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Estimating Cloth Simulation Parameters From Tag Information and Cusick Drape Test

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Figure 1: *The line below shows Cusick drape test results and tag info for five actual fabrics. The tag information includes fabric type, fiber composition, and density. Using this data, we estimated optimal simulation parameters (stretching and bending) to replicate each fabric's drape property in a cloth simulator. For verification, we made two dresses: one with real fabric and another with the estimated parameters in a virtual environment. In the upper line, each pair consists of a real-fabric dress (left) and a virtually simulated dress (right).*

Abstract

In recent years, the fashion apparel industry has been increasingly employing virtual simulations for the development of new products. The first step in virtual garment simulation involves identifying the optimal simulation parameters that accurately reproduce the drape properties of the actual fabric. Recent techniques advocate for a data-driven approach, estimating parameters from outcomes of a Cusick drape test. Such methods deviate from standard Cusick drape tests, introducing high-cost tools, which reduces practicality. Our research presents a more practical model, utilizing 2D silhouette images from the ISO-standardized Cusick drape test. Notably, while past models have shown limitations in estimating stretching parameters, our novel approach leverages the fabric's tag information including fabric type and fiber composition. Our proposed model functions as a cascaded system: first, it estimates stretching parameters using tag information, then, in the subsequent step, it considers the estimated stretching parameters alongside the fabric sample's Cusick drape test results to determine bending parameters. We validated our model against existing methods and applied it in practical scenarios, showing promising outcomes.
(see https://www.acm.org/publications/class-2012)

CCS Concepts
• Computing methodologies → Neural networks; Physical simulation;

1. Introduction

In recent years, the fashion apparel industry has increasingly turned to virtual simulations for new product development. Virtual gar-

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ment simulations enable designers to verify and enhance a product's design before creating the actual item. The primary step in this simulation process is to identify the ideal simulation parameters that mirror the actual fabric's physical properties chosen by the designer. Currently, the industry standard is to measure the fabric's physical properties directly using various tools, then determining the simulation parameters based on these measurements [KLG20]. Even for seasoned professionals, this process is considered a difficult and time-consuming task.

Lately, to address these problems, a data-driven approach has been proposed. This technique estimates simulation parameters by observing the results of a simple drape test on fabric samples, aiming for a simulation outcome that mirrors the drape test results. Prior studies have utilized methods similar to the Cusick drape test [Cus65]—a widely recognized method in the textile and cloth industry, corroborated by multiple research endeavors to have a significant correlation with various fabric properties [SCCE13; HC98]. Our study also builds upon these foundations, introducing a novel methodology utilizing the Cusick drape test to estimate simulation parameters.

However, many past studies did not strictly adhere to the original Cusick drape test method. Instead, they modified sample shapes or used advanced tools like 3D scanners or depth cameras to measure the three-dimensional shape of the drape. This addition of high-cost equipment and complex measurement processes diminishes the method's practicality. We present a new estimation model that assesses 2D silhouette images of the drape, taken following the ISO-standardized Cusick drape test procedure [08]. Therefore, our method holds the advantage of being seamlessly applicable using existing Cusick drape test equipment.

One limitation of the Cusick drape test in estimating simulation parameters is its weak correlation with a fabric's stretching stiffness. Due to this limitation, [FHXW22] suggested models that fix stretching-related simulation parameters, focusing only on estimating parameters related to bending. However, even if it is challenging to determine stretching parameters from draping results, changes in these parameters significantly influence the drape test simulation results. In other words, even if bending parameters remain consistent, varying stretching parameters can lead to different draping simulation outcomes. Hence, models that estimate bending parameters from draping results without considering stretching parameters inevitably have limitations in accuracy.

To address this, we propose leveraging fabric tag information, which includes details like fabric type and fiber composition. This tag data is routinely consulted by designers during fabric selection and is easily accessible. Therefore, its inclusion does not compromise the practicality of the existing method. Our proposed model functions as a cascaded system: first, it estimates stretching parameters using tag information, then, in the subsequent step, it considers the estimated stretching parameters alongside the Cusick drape test results to determine bending parameters (see Fig. 6). This approach factors in the influence of stretching properties from draping results, enhancing the accuracy of bending parameter estimation. To our knowledge, no attempts have been made to derive simulation parameters from tag information, primarily due to challenges in data acquisition. However, recent digital fabric services, notably VMOD, offer optimized simulation parameters along with tag details [Swa22]. We utilized data for about 5000 real fabrics from VMOD in our work.

To validate the efficacy of our model, we compared outcomes where the drape test results were measured as a 3D shape (as in prior methods) to those where results were measured as 2D silhouettes (as in our approach). Furthermore, we compared the accuracy of bending parameter estimations when using and not using the inferred simulation parameters from tag information. Finally, to demonstrate practical application, we created dresses using various real fabrics, compared virtual garments made with our estimated simulation parameters, and analyzed the visual differences

2. Background

Cloth simulation technology has undergone significant advancements aimed at increasing calculation stability, accelerating simulations, and expanding the range of expressions. Implicit time integration methods, such as stable integration methods proposed by various authors [CK02; VM05; LBOK13], have improved integration stability. Additionally, IPC (Incremental Potential Contact)-based methods have improved collision stability [LKJ21]. For faster simulations, the projective dynamics method [BML*14] and GPU-based solvers [TTN*13; LTT*20] have been proposed. Recently, deep learning-based simulations have been introduced to achieve real-time and high-accuracy simulations [OLL18; BME22].

There have been significant efforts towards expanding the expressiveness of simulations. The range of expressiveness in a typical mass-spring model is primarily determined by the definition of stiffness models. The stiffness model has evolved from a linear isotropic model to a non-linear anisotropic model to improve expressiveness [VMF09; WOR11]. In this study, we address the problem of estimating simulation parameters for the anisotropic nonlinear model. On the other hand, efforts are also underway to simulate specific types of fabric that are difficult to represent using the mass-spring model. Yarn-level simulation methods have been proposed to simulate the detailed characteristics of knit fabrics[KJM08; CLMO14; SNW20; SSL*22].

The development of cloth simulation technologies has made virtual cloth simulation a widely used tool in the apparel industry for developing new fashion products. Consequently, there is a growing demand for a practical and reliable method to find sets of simulation parameters that can accurately reproduce the mechanical properties of specific real-world fabrics under given simulator conditions. Recently, a learning-based approach was proposed to estimate simulation parameters from a static drape test, which offers practicality and accuracy [JC20; FHXW22; RPCG23].

2.1. Drape Test

Fabric properties are crucial for designers to choose the right fabric for a garment. The physical or mechanical properties of fabrics are often used to classify and index them based on their characteristics. The KES-F [KN89] and the FAST system [Min95] are specialized devices for measuring the physical properties of fabrics. However, for the average cloth designer, these physical measures do not help in comparing different fabrics or choosing the right fabric for a particular garment. The drape properties of fabrics have gained more attention in the apparel industry than their physical properties.

The Cusick drape test [Cus65] is the most widely used drape measurement method. This method observes the drape shape by placing a circular fabric specimen on a circular disk. In Cusick's original method, a 2D image of the drape projected on the horizontal plane is recorded by rotoscoping. The drape image can be used as a visual index representing the drape property intuitively. Various numerical indicators, such as drape area ratio, wrinkle depth, and wrinkle wave amplitude, have been introduced by quantifying the drape images [CCV17]. Cusick's method has evolved to measure dynamic drape properties and to analyze the 3D shape of drapes [MY03; Hal06; KLPE08; GZ14].

Studies have investigated the correlation between drape and mechanical properties in textile engineering. The literature has shown that most bending mechanical properties correlate highly with drape properties, although this is the case for only some tensile mechanical properties. Sanad et al. [SCCE13] investigated the correlation between measures of the FAST system and drape properties. In that study, most of the values measured by the cantilever showed a high correlation, and only some of those measured by the tensile device showed a high correlation with drape properties. Hu and Chan [HC98] investigated the correlation between measures of the KES-F and drape properties and showed that tensile linearity is highly correlated with drape properties.

Like the correlation between mechanical properties and drape properties, cloth simulation parameters correlate with simulated drape test results. Ju et al. [JC20] predicted drape test simulation results from simulation parameters, whereas Feng et al. [FHXW22] estimated bending parameters from actual drape test results. Both methods performed drape tests using square samples, not the circular ones defined in Cusick's method. In this study, we demonstrate that circular specimens are more advantageous than square ones for parameter estimation by analyzing massive drape test simulation results.

2.2. Estimating Simulation Parameters

One common approach to obtain simulation parameters for a specific fabric is to measure its mechanical properties using specialized devices such as KES-F or FAST systems, and then convert the measurements into parameters defined for the given simulator [BHW94]. However, this method has some limitations, including the high cost of equipment and the imperfections of the simulators, which may result in inaccurate parameter conversion. To address these limitations, software providers have developed specialized measurement devices and conversion programs for their simulators [CLO20]. Nonetheless, even with these tools, manual parameter tuning may still be necessary to reproduce the drape properties of the target fabric [JKL*22].

Optimization approaches offer an automated solution to parameter tuning. Bhat et al.[BTH*03] optimized simulation parameters for a hanging drape video, while Wang et al.[WOR11] and Miguel et al.[MBT*12] applied artificial force to a specimen of the target fabric to deform it, and then optimized the simulation parameters to reproduce the same deformations with the same force in the simulation. Other researchers optimized simulation parameters using feature vectors extracted from images of drape tests[MRMŽ12] or the drape shape in photos of people wearing clothes [YPA*18]. However, optimization approaches have some drawbacks, such as long computation times and sensitivity to the initial parameter values.

Recently, researchers have proposed learning-based approaches to enhance the accuracy and practicality of parameter estimation. Methods have been introduced for estimating simulation parameters by observing dynamic changes such as fabric fluttering in the wind [BTH*03; BXBF13; YLL17], and for estimating stretching properties by observing shape changes when artificial force is applied to a specimen [WOR11; MBT*12; RPCG23]. Among these, a method focusing on practicality and user convenience is to train a model to estimate simulation parameters from a single static drape test result [JC20; FHXW22]. Although such studies have shown excellent performance, relying solely on a single static drape test has limitations, as there is not a one-to-one correspondence between simulation parameters and static drape. To improve this limitation, this study proposes a method of estimating parameters using tag information that is readily available when purchasing fabric, in addition to drape test results.

3. Simulation Model and Parameters

Our cloth simulation is based primarily on the mass-spring model proposed by Baraff and Witkin in 1998 [BW98]. This model utilizes various spring-like energies, such as stretching and bending, to connect cloth particles. To achieve stable integration, we use the BDF-2 implicit integration method [CK02]. We present an extension of the original fabric model to accommodate a variety of real-world fabric materials for our cloth simulation. Here, we describe each simulation parameter, and the details are described in the Supplementary Material.

Stretching Stiffness The original Baraff-Witkin formulation uses a constant stiffness value for the stretching springs, but real-world cloth exhibits non-linear tendencies. Therefore, we modify the stiffness to be a function of the length scale l_i for each basis direction $i = u, v, h$, weft, warp, and bias, respectively. Our analysis from the stretching property data measured from 5,000 actual fabric samples (see Section 4) revealed that the exponential function best fits the nonlinear relationship between the length scale and the stiffness. Therefore, we define the stretching stiffness function, $k_i(l_i)$, as follows:

$$k_i(l_i) = \alpha_i \exp(\beta_i(\frac{l_i}{\bar{l}_i} - 1)), \tag{1}$$

where $\bar{l}_i$ is the rest length of the stretching spring in the ith direction.

Bending Stiffness We define an anisotropic non-linear bending energy term calculated for each bending wing (comprised of two adjacent triangles). We model the bending stiffness to be a piecewise constant function of the bending angle θ,. The bending stiffness energy term of the jth piece, k^j, is interpolated from the three bending stiffness values k_u^j, k_v^j, and $k_h^j(\theta)$, depending on the folding direction of the bending wing. To keep the model simple, we limit the number of pieces in the function to a maximum of two and fix the threshold angle switching between k^0 and k^1 at 15 degrees. k^1 is defined as a multiplication of scalar factor s_b and k^0. For more information about our cloth model, please refer to the Supplementary Material.

We aim to estimate the 12 simulation parameters defined above. The stretching parameters, P_s, and the bending parameters, P_b, are defined as follows:

$$P_s = \{\alpha_u, \alpha_v, \alpha_h, \beta_u, \beta_v, \beta_h\} \tag{2}$$

$$P_b = \{k_{bu}^0, k_{bv}^0, k_{bh}^0, s_{bu}, s_{bv}, s_{bh}\} \tag{3}$$

4. Fabric Data

We have acquired a comprehensive dataset, known as 5K–DATA, encompassing around 5,000 real fabrics, all of which are commercially available and were sourced from VMOD. This dataset not only includes tag information for each fabric but also features simulation parameter data, meticulously optimized by experts, tailored for each specific fabric. These fabrics are categorized into 64 distinct types, and across all these fabric types, there are 37 unique fiber types represented. This dataset showcases a diverse range of fabrics, each with its unique characteristics. For more detailed information on the distribution of fabric types and fibers within the 5K–DATA, please refer to the supplementary materials provided.

We conducted the Cusick drape test on 500 randomly selected fabrics from the entire data set and scanned the 3D geometry for analysis. From that, we made the following observations:

- Circular specimens exhibit higher visual diversity in the drape test compared to square specimens. As a result, circular specimens are recommended for accurate estimation of bending parameters (refer to Section 5.1 for details).
- The stretching stiffness of a fabric has a significant impact on the results of the drape test. Therefore, it should be taken into consideration while estimating the bending parameters from the test results. Further details are provided in Section 6.2.1.
- The stretching parameters of a fabric are correlated with its basic information. Therefore, it is possible to regress the stretching parameters based on the fabric's basic information, achieving an acceptable accuracy score. Refer to Section 6.1 for more information.

5. Cusick Drape Test

We employed the original Cusick drape test, which has the advantage of accepting the results of abundant existing literature, despite the existence of many variations. The test involves observing the wrinkles on the unsupported part of a circular specimen with a diameter of 30 cm, when it is placed on a circular disk with a diameter of 18 cm.

5.1. Circular vs. Square

Previous studies have utilized square samples for parameter estimation problems due to their ease of cutting and clarity in distinguishing the weft and warp directions [JC20; FHXW22]. However, square specimens in drape tests often result in a cross shape, as the four corner areas of the unsupported part are wider than other unsupported areas and are consequently more affected by gravity. This leads to limited visual variability across the overall drape shape.

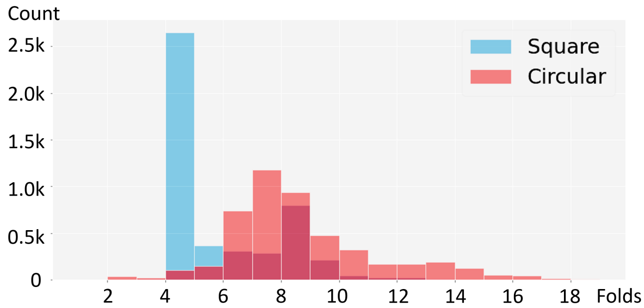
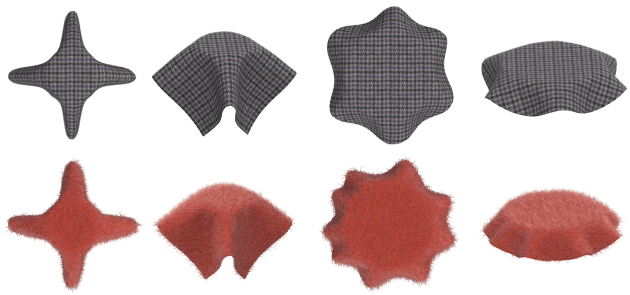


Figure 2: *Histograms of the number of folds of drape tests using square and circular specimens.*



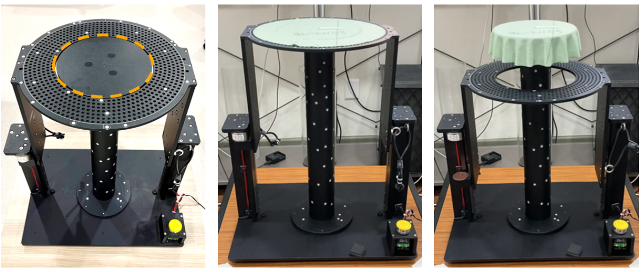
(a) *Square specimen.* **(b)** *Circular specimen.*

Figure 3: *Comparison of drape test results for FLANNEL type, wool 100% fabric (top) and CLIP JACQUARD type, polyester 100% fabric (bottom). When using square specimens, both fabrics formed a similar cross shape, whereas entirely different shapes were formed with circular specimens.*

We simulated drape tests using square and circular specimens for the parameter sets of 5K–DATA and counted the number of folds in each drape. Fig.2 displays the histogram. An overwhelming number of cases had four folds when using square specimens. In contrast, the number of folds was relatively evenly distributed when using circular specimens. Consequently, the visual variability of drape results for different fabrics was higher with circular specimens than square specimens. Fig.3 presents specific examples of drape tests using square and circular specimens for two distinct fabrics. When using square specimens, both fabrics formed a similar cross shape, whereas entirely different shapes were formed with circular specimens.

5.2. Test Device for Consistency

Drape test results are influenced by various factors beyond the physical properties of the fabric itself. Notably, the initial state of the specimen has a significant impact on the final result. Consequently, it is essential to avoid holding and dropping the sample by



(a) *Our draping device* **(b)** *Initial state* **(c)** *Final state*

Figure 4: *(a) Our custom-designed Cusick Draping Device. Our device features a dropping disk densely perforated with holes to allow air passage during descent. (b) shows the initial setup of the draping experiment. (c) depicts the completion of the experiment following the descent of the dropping disk.*

hand to prevent artificial wrinkles from forming on the part held by the fingers and to eliminate the likelihood of obtaining different results based on the holding position. To address these issues and maximize the consistency of experimental results, we developed the device. In the experiment's initial state, both supporting and dropping disks are at the same height, enabling the entire circular specimen to be spread flat and placed on the disks, as demonstrated in Fig.4b. Upon pressing the yellow button, the dropping disk begins free-falling, and concurrently, the entire unsupported area of the specimen also free-falls (see Fig.4c). The entire device is constructed from anti-static plastic, and we drilled densely spaced small holes in the dropping disk to minimize the effect of air pressure during the drop (see Fig.4a).

Fig. 5 presents a comparative analysis captured using a high-speed camera, contrasting the utilization of a solid dropping disk (non perforated) and a perforated dropping disk. We conducted the experiment using the same fabric for both disks. To ensure the precise positioning of the specimen on the supporting disk, we magnetically affixed it to the top of the supporting disk. This method effectively immobilizes the fabric between the supporting disk and the magnet, preventing any displacement during repeated experimental runs, even when using replacement disks. Observations at 70 milliseconds from the start of the experiment reveal notable differences. With the solid disk, air pockets formed between the specimen and the disk, as indicated by green arrows. The rest of the fabric clung to the disk due to air pressure, as highlighted by red arrows. Consequently, this led to unwanted wrinkling (not indicative of free fall) as air injection concentrated through these air pockets, which is evident in the area circled at the 90 milliseconds mark. The location of these air pockets varied with each trial, affecting the consistency of the experiment. In contrast, the use of a perforated disk allowed air to enter beneath the specimen right from the onset of the experiment. This resulted in a uniform detachment of the entire fabric from the disk, allowing it to undergo independent free fall right from the moment the disk commenced its drop. This significant difference was also evident in the final draping outcomes, as observed in the final states, showcasing a notable disparity in the end results of the draping process with different disks.

To confirm the consistency of drape test results, we requested multiple participants to perform the drape test for the same fabric. In each test, participants completed the entire process independently, from cutting the fabric into a circular shape to placing and dropping the specimen. Although the specimen shapes may have slightly varied, the results remained relatively consistent.

5.3. Drape Test Simulation

The focus of our simulations was on accuracy rather than speed, and we employed a non-adaptive triangular mesh to represent the fabric specimen. This mesh consisted of 30,306 vertices, with a maximum spacing of less than 5mm between them, forming 10,102 triangles. During the simulation, the timestep was consistently maintained at 0.03 seconds. The initial setup involved the circular specimen mesh being fully spread out, parallel to the supporting disk, and elevated 2 cm above it. The simulation concluded when all vertices came to a stop, indicated by their speed dropping below a predefined threshold. Any simulation where the specimen fell to the ground was deemed unstable and excluded from our data.

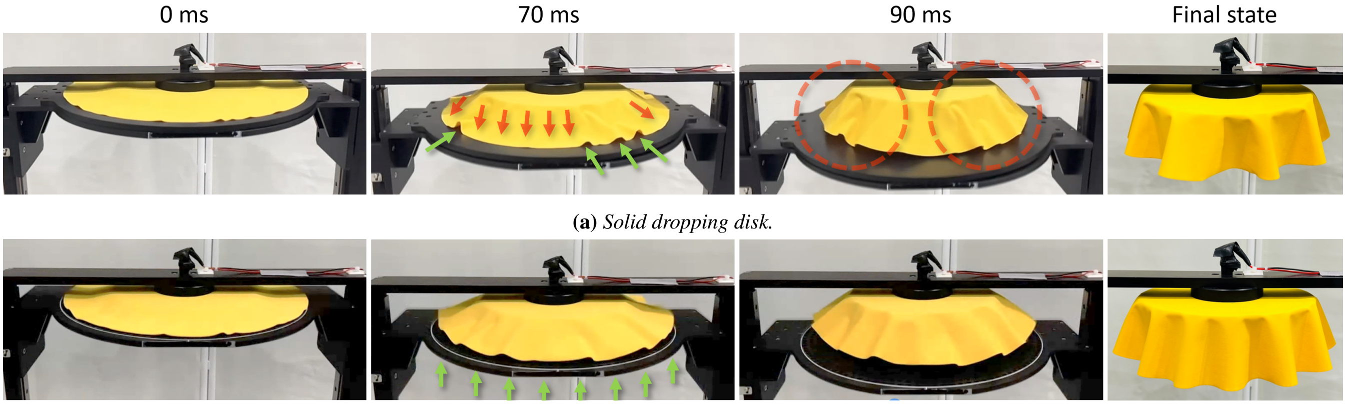
6. Method

Based on these findings, we developed a cascaded model for estimating the stretching and bending parameters of a target fabric. The overview of the model is presented in Figure 6. Our model takes tag information and results of the Cusick drape test as input. First, the stretching parameters are estimated using k-nearest neighbor (kNN) regression based on the type and fiber composition information in the tag data (pink area in Figure 6). Next, the bending parameters are estimated using the estimated stretching parameters and the 2D silhouette image of the Cusick drape test results (green area in Figure 6). To reduce the number of parameters involved in the model, we normalized the stiffness values of the training data by dividing them by the density. This method was proposed in [FHXW22] and has the advantage of not having to consider the diversity of density in the training data collection. As a result, the required amount of training data can be reduced. Therefore, the original stiffness is restored by multiplying the density to the stiffness of the estimated result.

6.1. Stretching Regression Model

In our study, we employed regression analysis to determine the relationship between the stretching parameters and the tag information of various fabrics. This approach was grounded on several key assumptions:

1. Fabric types exhibit consistent patterns and structures, implying that the *type of fabric* significantly influences its anisotropic properties.
2. In the case of woven fabrics, the strength of the fibers plays a crucial role in defining their tensile properties. Hence, there is a strong correlation between the stretching parameters and the *composition of the fabric*.
3. For nonwoven fabrics, the pattern or structure of the fabric markedly impacts its tensile characteristics. Thus, the *type of fabric* is also a critical factor in determining the stretching parameters.



(a) *Solid dropping disk.*

(b) *Perforated dropping disk.*

Figure 5: *Comparison of draping tests using solid (a) and perforated (b) disks. With the solid disk, the specimen adheres to the disk due to air pressure (red arrows) and forms air pockets (green arrows), evident at 70 ms. This results in unexpected wrinkles as seen at 90 ms. Conversely, the perforated disk promotes uniform air flow from the outset, ensuring consistent fabric detachment and free fall.*

4. Variations in fiber strength, even within the same type, can be distinguished by considering the *density* of the fabric.

The stress-strain response curves for different fabric orientations (weft, warp, and bias) are presented in Fig. 7. These curves were derived from an analysis of four fabric groups having identical types and compositions from the 5K–DATA dataset. The observed patterns confirm our hypotheses regarding the anisotropic properties of fabrics. Fabrics sharing the same type and composition exhibited similar anisotropic behaviors.

For the regression analysis, we utilized a k-Nearest Neighbors (kNN) model to fit the stretching parameters based on fabric type and composition. The number of neighbors, k, was set to 50. Fabric types were represented using one-hot encoding with 64 dimensions, while the composition ratios were encoded as a vector representing the ratio values for each fiber type, encompassing 37 dimensions. To normalize the stretching parameters, we first adjusted them based on fabric density and then applied log-normalization.

6.2. Bending Estimation Model

For bending estimation, we train a neural network model. The inputs consist of the target fabric's stretching parameters, which are estimated by the regression model in Section 6.1, and the encoded latent vector of the silhouette image of the drape test result. The output is the bending parameters of the target fabric, normalized by dividing them by the density followed by log-normalization. The neural network is a MLP (multi-layer perceptron) model with two hidden layers with 512 nodes and ReLU activation layers following each layer. In our experiments, we trained for 100 epochs with a batch size of 64 and a learning rate of 0.01 using the Adam optimizer [KA*15]. The mean squared error loss function was used as the loss function.

6.2.1. Stretching Parameter Input

To confirm the impact of stretching parameters on the drape test, we compared the actual drape test results for two fabrics with similar bending properties and different stretching parameters. Consequently, we could easily identify cases with significant differences in drape shapes. Fig. 8 presents two pairs of examples. The difference of the bending parameters between each pair is less than 3%, whereas the difference of the stretching parameters is more than 10% after applying log min-max normalization. Based on these observations, we use the stretching parameters as inputs for the bending parameter estimation model to account for the influence of stretching parameters on the drape shape.

6.2.2. Drape Input

We use the silhouette 256 by 256 image captured from the top view of the drape test result as the input data. To align the weft and warp directions of the fabric with the edges of the image accurately, we placed an ArUco marker [GMMM14] on the fabric specimen before taking the photo (see Fig. 9). The marker was used to correct the direction, scale and distortion of the image caused by the camera lens and position. To make it easier to distinguish the fabric from the background, we used a green or red background for the drape test.

User convenience was the main reason for using 2D silhouette images instead of 3D drape shapes. The original Cusick device was designed to obtain the silhouette image of the drape shape from the top view. Therefore, any data obtained from the device can be used as input data for our model. Furthermore, silhouette images can be easily obtained from general RGB photos, making them more efficient in cost and time than 3D scans or depth images. In addition, using 3D drapes does not significantly improve the accuracy of bending parameter estimation in our experiments. In Section 7, we compare the estimation performance of cases using 3D drape and silhouette images.

We encode the silhouette image into a 512-dimensional latent vector using an autoencoder. The encoder and decoder comprise six convolutional layers and one fully connected layer. A pooling layer and a ReLU activation layer follow each convolutional layer.

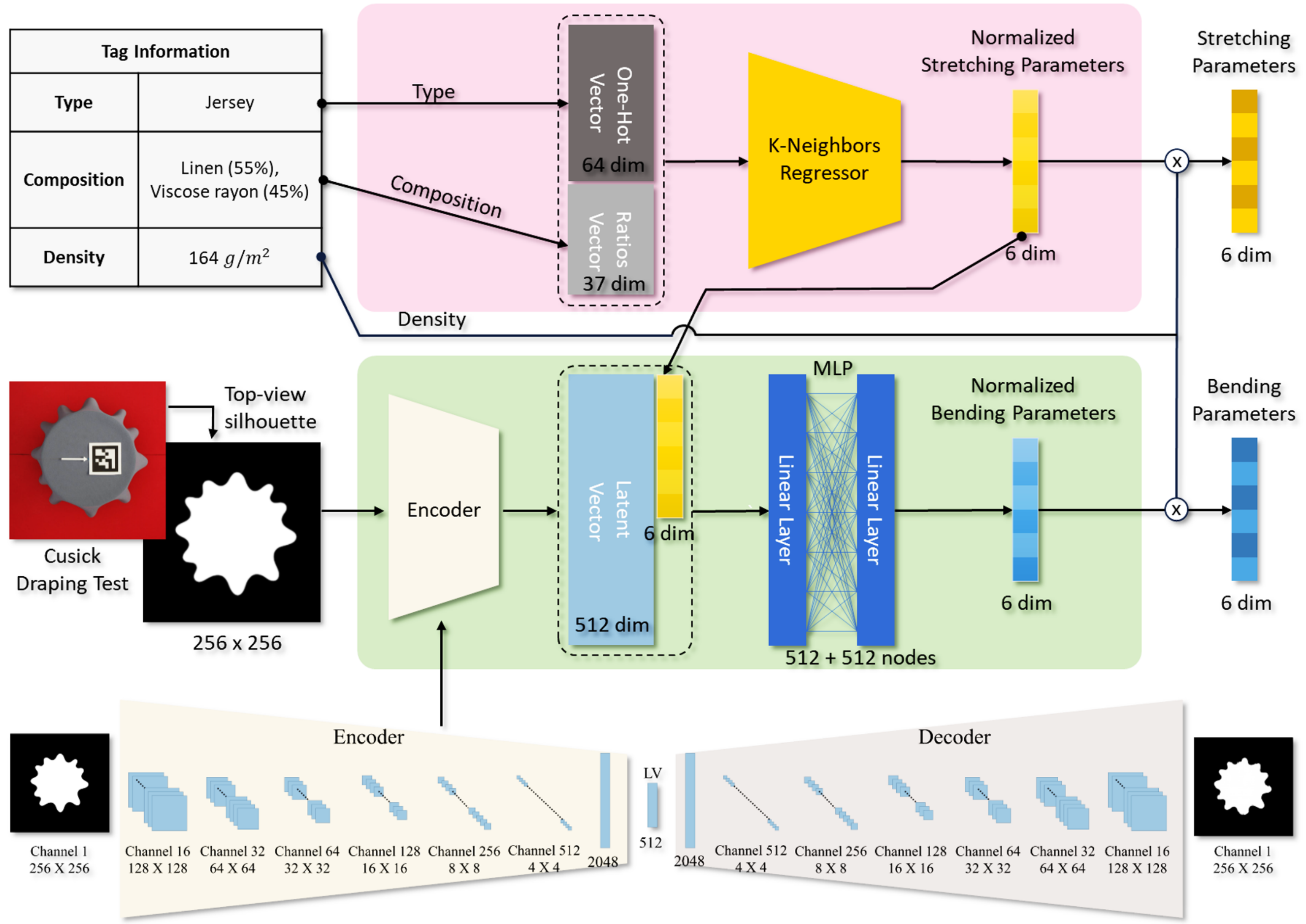


Figure 6: *Simulation Parameter Estimation Model. The model consists of two parts: the stretching regression model and the bending estimation model. The stretching regression model estimates the stretching parameters using the tag information. The bending estimation model estimates the bending parameters using the stretching parameters and the 2D silhouette image of the drape test result.*

For all the convolutional layers, the kernel size is three by three, and the stride is one. Each layer's detailed channel and pooling size is shown at the bottom of Fig. 6. We trained the autoencoder for 100 epochs with a batch size of 64 and a learning rate of 0.001 using the Adam optimizer [KA*15]. The loss function was the mean squared error between the input and output images.

6.3. Generating Training Data

We generate training data by sampling simulation parameters and simulating the drape test. The parameter space should include bending parameters for outputs and the corresponding stretching parameters for inputs. To ensure the validity of the sampled parameter set, we first fit a Gaussian mixture model (GMM) with the clustering number of 5 for the simulation parameters of 5K–DATA and then sample according to the probability distribution of the GMM [JC20]. For our experiments, 300,000 simulation parameter sets were sampled equally for each cluster using the GMM model to generate training data. The Cusick drape test was simulated with each parameter set. Each drape simulation result was projected onto a horizontal plane, converted into a silhouette picture, and used for the training of the autoencoder, and the encoded latent vector was used for the training of the bending parameter estimation model.

7. Experimental Results

To evaluate the performance of our model, we conducted a series of experiments using 5K–DATA. We first evaluated the accuracy of the stretching parameter estimation model, which is a k-nearest neighbor regression model. We split the 5K-DATA randomly into 10 folds and conducted a 10-fold evaluation. Table 1 shows the scores (the coefficient of determination, R^2 [CWJ21]) of the 10-fold evaluation.

The accuracy for the validation data was lower than that for the training data. However, as described in the following experiments, the estimated stretching parameters played a role in improving the accuracy of the bending parameter estimation, and ultimately, we obtained results that generated virtual clothes similar

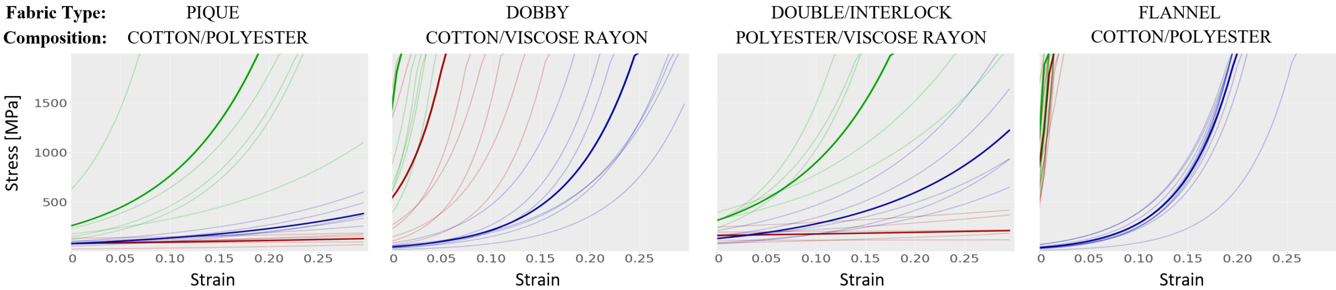
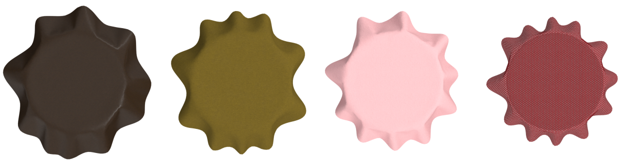


Figure 7: *Stress strain curves graphs for four group fabrics with the same type and composition. The red, green, and blue lines represent the graphs for weft, warp, and bias directions, respectively. The bold lines indicate the average graphs for each direction. The graphs of each direction for the same group are generally centered around the average graph.*

∼	(a) Left	(a) Right	(b) Left	(b) Right
α_u	1.000	0.653	0.411	0.722
α_u	1.000	0.774	0.575	1.000
α_h	1.000	0.643	0.488	0.786
β_u	0.812	0.091	0.288	0.000
β_v	1.000	0.489	0.455	0.740
β_h	0.463	0.336	0.385	0.197
k^0_{bu}	0.089	0.081	0.043	0.057
k^0_{bv}	0.450	0.422	0.359	0.389
k^0_{bh}	0.353	0.327	0.150	0.120
k^1_{bu}	0.088	0.079	0.042	0.056
k^1_{bv}	0.448	0.420	0.357	0.387
k^1_{bh}	0.351	0.325	0.149	0.119



(a) *DEWSPO & JERSEY* **(b)** *PLAIN WOVEN & MESH/TULLE*

Figure 8: *Two pairs of examples with similar bending stiffness and different stretching stiffness. This demonstrates that the change in stretching stiffness has a significant impact on the drape shape.*

Fold	Train (R^2)	Val. (R^2)	Fold	Train (R^2)	Val. (R^2)
1	0.820	0.599	2	0.820	0.607
3	0.818	0.651	4	0.821	0.629
5	0.824	0.590	6	0.816	0.606
7	0.819	0.583	8	0.819	0.630
9	0.820	0.636	10	0.820	0.604

Table 1: *(R^2) scores of 10-folds evaluations for the stretching parameter estimation*

Input method	Train (R^2)	Val. (R^2)	Train (RMSE)	Val. (RMSE)
2DS+S (Ours)	**0.936**	**0.937**	**0.055**	**0.055**
2DS	0.825	0.823	0.090	0.091
3DC+S	**0.911**	**0.913**	**0.065**	**0.065**
3DC ([JC20])	0.809	0.808	0.094	0.095
3DI+S	**0.942**	**0.939**	**0.051**	**0.053**
3DI ([FHXW22])	0.824	0.817	0.089	0.091
3DD+S	**0.907**	**0.908**	**0.066**	**0.066**
3DD	0.755	0.755	0.106	0.107

Table 2: *Comparison accuracies between different input methods*

to real clothes. This is because the stretching parameters have little effect on the drape results when they change within a narrow range.

For the training of bending estimation model, we used the generated data from the simulations (refer to Section 6.3). We allocated 10% of the total data for use as validation data. We conducted a series of training with different input methods to validate the superiority of our proposed method. Table 2 summarizes the training scores. We compared four types of drape encoding methods: the first is the auto-encoded 2D silhouette (**2DS**); the second is the 3D boundary curve of the drape (**3DC**), as used in [JC20]; the third is the set of depth images taken form four different directions (**3DI**), as used in [FHXW22]; and the final is the auto-encoded 3D drape into a 512-dimensional latent space (**3DD**). For each drape encoding method, we tested with (**+S**) and without the stretching parameters as input. **2DS+S** represents our method. As shown in the scores, the accuracy of bending estimation was significantly reduced without the stretching parameters as input in all drape encoding cases. Moreover, using 3D data of the drape (**3DD** or **3DC**) as input did not improve the accuracy of the estimation. **3DI+S** shows similar performance to our method. However, 3DI+S uses depth images of the drape taken from multiple directions, whereas we use a single silhouette image. This demonstrates the practicality of our method. Figure 9 shows the comparisons of the three pairs of the actual fabric's Cusick drape result and the simulated result by the parameters estimated from our model. More examples are shown in the Supplementary Material.

We benchmarked the performance of our proposed learning model against the model suggested by Ju et al. [JC20], chosen for its similarity to our approach in estimating both stretching and bending parameters concurrently from a Cusick-like drape test result. Ju et al.'s model utilizes two separate MLPs for estimating stretch and bending parameters, each MLP featuring three hidden layers with dimensions of 4096, 8192, and 512 neurons, respectively. The input layer processes a 3D boundary curve (3DC) scanned from a square specimen draping result. To adapt this model to our dataset, we modified the input layer to accommodate a 3DC from circular specimen draping and aligned the output layer with our defined parameters. Maintaining other conditions identical to the original experiment, we trained the model and assessed its accuracy. The results, presented in Table 3, demonstrate that while Ju et al.'s neural network model was initially tested only on linear parameter models, it significantly underperforms in estimating non-linear parameters compared to our method.

	Stretching		Bending	
Model	Train (R^2)	Val. (R^2)	Train (R^2)	Val. (R^2)
Ours	0.820	0.614	0.936	0.937
[JC20]	0.611	0.373	0.851	0.747

Table 3: *Comparison of the accuracy between our model and the model proposed by [JC20]. The stretching accuracy values of our model are the averages of the values in Table 1.*

To validate the utility and fidelity of our methods, we estimated the simulation parameters for various actual fabrics. Then, we created pairs of the same garment, one using the actual fabrics in the real world and the other using the estimated parameters in the virtual world. We created two types of garments: a one-piece dress (see Fig.1) and a flared skirt (see Fig.10). As shown in the figures, the drape property of each actual garment is reproduced very similarly in the virtual garment with the simulation parameters estimated by our method. Please refer to the Supplementary Material for more examples.

8. Conclusion and Limitation

In this study, we presented a practical model for estimating stretching and bending parameters to simulate target fabrics. We proposed a cascade learning approach that uses fabric tag information in addition to the original Cusick drape test to improve the limitations of previous studies relying solely on the drape test while maintaining practicality. To obtain reliable training data, we acquired tag information and optimized simulation parameter data for 5,000 real fabrics. We demonstrated that the accuracy of bending parameter estimation is improved when considering stretching parameters. We also demonstrated that bending parameters can be estimated using 2D silhouette images without using 3D drape shapes. To demonstrate the utility of our method, we created a real garment using actual fabrics and a virtual garment using estimated parameters. We showed that the drape shape of the virtual garment simulated with the estimated parameters is very similar to that of the real garment.

8.1. Limited Fabric Tag Information

We utilized over 5,000 actual fabrics in our dataset, a number considerably larger than previous studies. However, this number still does not encompass the full diversity of fabrics found in the real world. For simulation parameter data and simulated drape data, we generated synthetic data through simulation. Yet, we faced challenges in finding a feasible method to produce synthetic data for fabric tag information. As a result, we had to rely on the given tag information. For estimating the stretching parameter, we employed a relatively simple kNN regression model, which inevitably had its limitations in terms of estimation accuracy.

Moreover, the distribution of our fabric dataset is skewed, favoring more commonly available samples. Some fabric types are underrepresented with only a handful of data points. For instance, we only have four samples of DOBBY MESH and two for ITV/MATTE JERSEY. This lack of representation hampers the efficiency of the estimation model, leading to lower parameter estimation accuracy for these categories.

To further understand the relationship between the size of the dataset and the accuracy of stretch parameter estimation, we conducted a series of experiments by systematically reducing the size of the 5K–DATA dataset. We randomly selected subsets of the data using a uniform distribution to create smaller datasets of 1/2, 1/4, and 1/6 of the original size. For each reduced dataset, we applied the same 10-fold cross-validation method to evaluate the average accuracy of our model. The results of these experiments are summarized in Table 4.

Data Size	Train (R^2)	Validation (R^2)
1/2	0.834	0.562
1/4	0.850	0.507
1/6	0.861	0.427

Table 4: *Average accuracy of the stretching parameter estimation model for different data sizes*

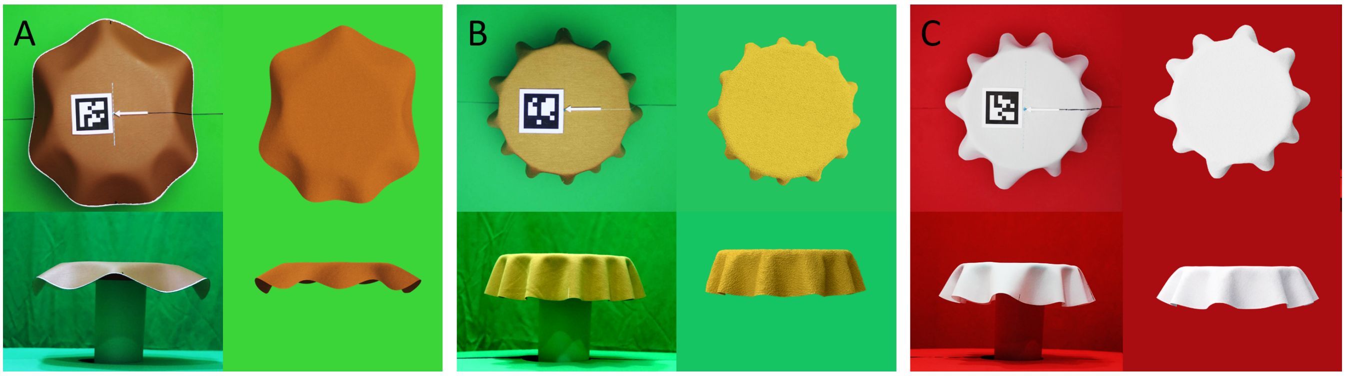
These results indicate a trend where the accuracy on validation data significantly increases with the increase in data size. This finding underscores the importance of having a larger dataset for more precise and reliable predictive modeling in fabric behavior analysis.

With the ongoing expansion of the digital fashion industry, organizations like VMOD, which gather data on actual fabric types, are on the rise. As these entities amass more data in the future, we anticipate being able to leverage it to collect a broader range of fabric tag information. Once we have ample data, we hope to use more intricate models for estimating the stretching parameter. Additionally, researching methods to generate reliable synthetic tag information could also be an intriguing avenue for future study.

8.2. Limited Cloth Simulation Model

The other notable limitation in our research is our sole focus on a specific cloth simulation model. Even though our used cloth simulator is grounded on Baraff and Witkin's widely recognized mass-spring model [BW98], it remains an assumption that our methodology would generalize efficiently across other similar cloth simulators. Direct empirical validation would be more conclusive.

Especially for fabric types that demand an entirely distinct cloth model for accurate draping representation, our approach may face



	Category	Sub Category	Type	Composition	Density (gsm)
A	Animal alternatives	Vegan leather	Vegan leather	Spandex / Elastane (100%)	340
B	Cut & Sew knit	Double	Ponte	Polyester (68%), Spandex / Elastane (2%), Viscose rayon (30%)	276
C	Woven	Plain	Crepe / CDC	Polyester (100%)	84

Figure 9: *Cusick drape examples. The left image in each pair is an actual fabric, and the right image is the simulated with simulation parameters estimated by our model. The table below shows the tag information of each fabric.*

challenges. Through various drape tests, we identified two drape shapes that are particularly hard to emulate owing to the simulator's inherent expressive constraints. The first pertains to the edge curling phenomenon observed in some knit fabrics. The left image in Fig.11a illustrates this phenomenon in a real fabric drape test. Conventional cloth simulators based on the mass-spring model find this phenomenon difficult to mimic. The right image in Fig.11a displays the results of our simulation using parameters determined by our methodology. While the overall shape bears resemblance, the edge curling phenomenon is not effectively replicated. Current research efforts, aimed at simulating the intricate dynamics occurring in knit patterns to replicate such phenomena, have been highlighted in [MPR18].

The other challenging case arises when there's a marked difference in the physical attributes between the left and right bias directions, as depicted in Fig.11b. This drape shape is hard to simulate, primarily because the majority of cloth simulators, ours included, presuppose identical properties in both bias directions. To asymmetrically define the bias direction, one would need to introduce multiple new parameters. This would lead to a drastic expansion in the dataset size necessary for both generation and training. This, indeed, presents an intriguing topic for future research

To validate and compare our method for a cloth simulator with an entirely new parameter model, an additional dataset of 5,000 entries optimized for that parameter model is required. We anticipate that by collaborating with institutions that digitize fabrics, such as VMOD, we can verify and enhance the effectiveness of our approach for future cloth simulation models.

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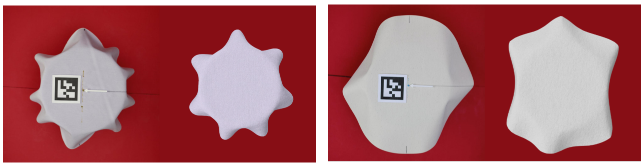
	Category	Sub Category	Type	Composition	Density (gsm)
A	Woven	Twill	Denim	Cotton (100%)	400
B	Cut & Sew knit	Pile	Fleece	Cotton (22%), Polyester (78%)	360
C	Cut & Sew knit	Single	Jersey	Polyester (30%), TENCEL™ (70%)	115
D	Cut & Sew knit	Pile	French terry	Cotton (100%)	188
E	Woven	Plain	Chambray / Oxford	Cotton (100%)	200
F	Woven	Plain	Poplin	Nylon (59%), Supima cotton (41%)	60
G	Cut & Sew knit	Texture	Pique	Cotton (20%), Polyester (80%)	248
H	Woven	Plain	Dewspo	Nylon (50%), Polyester (50%)	72
I	Woven	Plain	Chiffon	Polyester (100%)	80

Figure 10: *Flared skirt examples. The left image in each pair is a skirt made of actual fabric, and the right image is a skirt simulated with virtual fabric using the simulation parameters estimated by our model. The table below shows the tag information of each fabric.*



(a) *Curly boundary* **(b)** *Asymmetric bias properties*

Figure 11: *For each example, the left image is the drape test result of the actual fabric, and the right image is the simulated result with simulation parameters estimated by our method.*

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