Actual Fabric Digitalization

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Abstract

3D computer-aided design systems have emerged as promising techniques for garment learning processing, virtual shopping, and fashion shows within the fashion and garment industries. However, the effective application of these digital systems requires precise characterization of fabrics, garment patterns, and human body shapes that accurately reflect the appearance and behavior of the garments in a digital environment. Creating a 3D digital garment involves inputting the corresponding digital fabric properties. Nevertheless, obtaining these measurements can be complex, often necessitating the involvement of well-trained technicians. In this study, our focus is on a simplified and automated technique for digitizing real fabrics. Specifically, we aim to find the most relevant digital fabric in the database of a 3D software by employing image processing and machine learning techniques to drape images.

Mots clefs

Machine learning, Drape parameter, Garment design

1 Introduction

Industry 4.0 represents a significant challenge and opportunity for technology companies, as it has the potential to contribute to the advancement of humanity. Clothing is a fundamental human need, and thus, competition among companies in the garment industry must adapt to this revolution with flexibility and responsiveness in order to satisfy a broad range of potential market demands. In textile industry, the choice of fabrics plays a crucial role in determining the wearer's comfort and garment style by their various mechanical properties. Specifically, the drape of fabric is one of the most important mechanical properties that can significantly impact on interactions of a garment with the body. It is related to comfort feeling of the wearer and aesthetics of the design style (e.g. well fitted or not). Various studies have been conducted to develop drapemeters with the aim of simplifying the measurement process, (presented in [1, 2, 3]), improving the accuracy of fabric properties, reducing the reliance on operator expertise, and proposing alternative fabric drape parameters.

Creating a 3D digital garment requires inputs of the corresponding digital fabric properties. These properties can be directly measured using physical instruments, such as Kawabata Evaluation System (KES) [4] and Fabric Assurance by Simple Testing (FAST) [5]. However, these measurements are rather complex and require interventions of well-trained technicians. In this situation, to facilitate the creation of a 3D garment, it is imperative to select a suitable digital fabric already existing in an extensive fabric database linked to the 3D software (for example Lectra, Toray-Acs, Gerber, Investronica, Optitex, etc...), in which the technical parameters (drape parameters, optical parameters, and mechanical parameters) of the representative fabrics are complete [6].

In this study, we focus on a simplified and automated technique for digitizing real fabric through the use of image processing and machine learning techniques based on a software fabric database. First, for a real fabric, the user (designer) extracts its drape image with the use of a simple drape meter (Cusick Drapemeter [7]) and extracts drape parameters by using image analysis. Then, clustering fabric in the software database to choose the most relevant group. The closest digital fabric present in the fabric software database is predicted using machine learning concerning drape image features as the input. The rest of the paper is organized as follows. Section 2 presents the method to predict the closest fabric including three main steps based on image processing and machine learning techniques. Then the results are discussed in Section 3. Finally, the conclusion is briefly discussed in Section 4.

2 Methodology

In this section, the process of digitalizing actual fabric is presented. The concept is a new fabric that has no information about mechanical properties can be assigned with the most relevant fabric found in a software database, (e.g. Lectra database). The overall progress includes three main steps. In the first step, a drape image of a real fabric is processed by extracting contour information using image processing techniques to estimate five drape parameters (explained in Section 2.2). Then, digital fabrics in the software database are clustered into different groups based on their drape parameters and the number of nodes in the real fabric to determine the closest group in Section 2.3. Finally, a number of classification machine learning models are applied to identify the closest digital fabric based on the output of previous steps in Section 2.4. In addition, the software database of fabric is also introduced in Section 2.1.

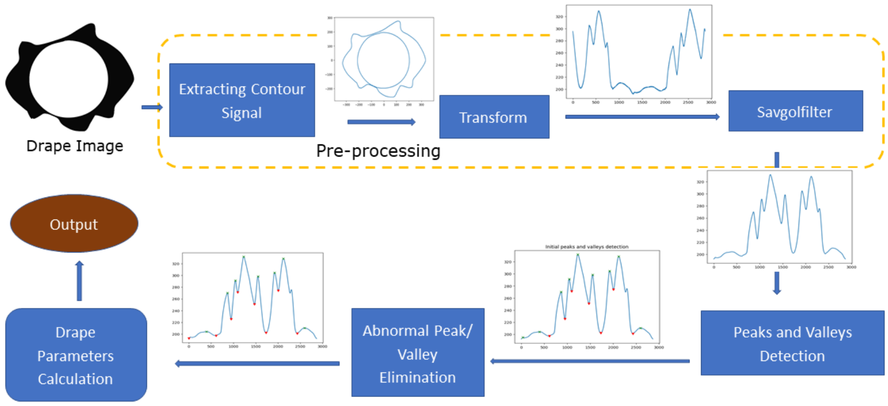

FIGURE 1 – *The process of Drape Parameter Estimation*

2.1 Fabric database preparation

In the 3D CAD software, the technical parameters of a fabric are considered as inputs to the garment simulation system. These technical parameters include a number of basic parameters (e.g. thickness, weight), optical parameters (e.g. texture (weft and warp structure) and color), mechanical parameters (e.g. bending, shearing, tensile), etc. For instance, in the Lectra Modaris 3D Fit CAD software, the database is composed of 111 digital fabrics with drape images (extracted by the use of a simple drape meter (Cusick Drapemeter [7])) and 23 technical parameters (i.e. drape shape, number of fabric, AA, AD, MP, MV, NoP, weight, commercial name, composition, thickness, weave, warp/weft texture, warp bending, weft bending, drape coefficient, number of plies, CisT, CisC, FlexT, FlexC, Colors, Patterns), which is capable of covering almost all ranges of fabrics used in garment design.

2.2 Drape Parameter Estimation based on Image processing

This section outlines the methodology for calculating drape parameters, which comprise the average amplitude (AA), average distance (AD), maximum peak (MP), minimum valley (MV), and number of peaks (NoP). The parameters can be determined by analyzing the contour signal which is extracted from drape image. First, the definition of the parameters is introduced, followed by technical image processing pipeline.

Drape parameter definition. The initial presentation of the extracted contour is in the Polar coordinate system, then the contour signal is transformed to the Cartesian coordinate system to facilitate the analysis, as illustrated in Figure 2. The number of peaks (NoP) in the signal can be determined by counting the number of signal periods, which is equivalent to the number of valleys. Specifically, in Figure 2, the orange, red, blue, and black arrow corresponds to the AD, MP, MV, and AA, respectively. **MP** and **MV** is the distance from zero to the highest and lowest point, respectively. **AD** is the average distance from zero or the mean

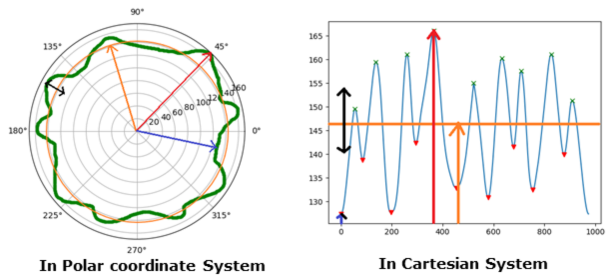

FIGURE 2 – *Contour signal in different space*

of the contour signal. **AA** is the average amplitude of each node in the signal. The unit of these parameters is pixel. The AA and AD from contour signal to the center point of circle are computed using the following formula 1 :

$$
\begin{aligned}
AA &= \frac{1}{n}\sum_{i=1}^{n}\frac{p_i - v_i}{2} \\
AD &= \frac{1}{n}\sum_{i=1}^{n}\frac{p_i + v_i}{2}
\end{aligned}
\tag{1}
$$

where n : number of peaks (number of valleys); p_i, v_i : dimension of peak and dimension of valley i, respectively. In addition, the maximum peak and minimum valley are also considered in dimension of signal.

Drape Parameters Estimation Process. The process of estimating drape parameters includes four steps, namely *Pre-processing*, *Peaks and valleys Detection*, *Abnormal Elimination*, and *Drape parameters Calculation*, as depicted in Figure 1.

The ***pre-processing*** step plays a critical role in extracting the raw contour information that forms the basis of drape parameter computation. The raw contour signal is extracted in Polar coordinates, achieved through the detection of changes in color or intensity. The next step involves transforming the raw signal into the Cartesian system, taking

into consideration the function of the distance from the center point to the contour line.
Peaks and Valleys Detection : After extracting the clean contour signal, an algorithm for peaks detection (presented in [8]) is applied to detect the number and position of peaks and valleys.
Abnormal peak/valley Elimination : A node consists of a peak and a valley. Therefore, the process of finding the number of nodes can be considered as the process of detecting peaks and valleys. In some cases, the detected peak or valley may not be considered as a node in the context of the whole signal. For example, some peaks or valleys may be considered as leakage or abnormal rather than true peaks or valleys. To address this, our algorithm detects pairs of peaks and valleys whose distance is less than a certain defined threshold and considers them as abnormal peaks or valleys. Additionally, we assume that the number of peaks and valleys is equal and that a peak is always followed by a valley. Consequently, any peak or valley that does not satisfy this condition will be removed.
Drape Parameters Calculation : Upon the removal of the outlier noise, the drape parameters are calculated in accordance with the procedures outlined in Section 2.2.

2.3 Clustering Process

The idea is to cluster the existing digital fabrics (in software database) into different clusters based on the similarity of their drape parameters to identify the group that is the closest to the real fabric (closet group), as shown in Figure 3. To simplify the process, we reduce the number of digital fabrics based on the estimated NoP parameter (calculated in Section 2.2). Suppose the estimated NoP parameter is N. The idea is to choose all digital fabrics that have NoP = [N-1, N, N+1]. Then, these fabrics are clustered using the K-means algorithm and Principal Component Analysis (PCA).

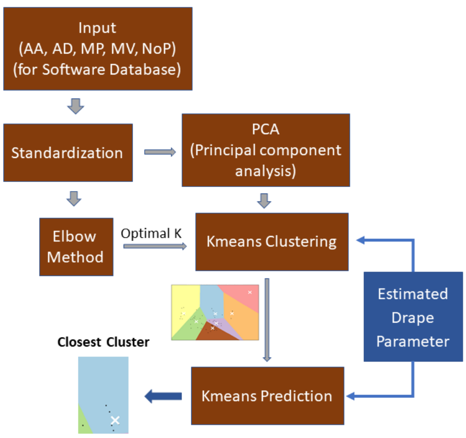

FIGURE 3 – *The process of Clustering software database*

K-means (presented in [9]) is an unsupervised machine learning algorithm that divides data into a specified number of clusters, where it partitions a set of fabrics based on the four attributes, namely AA, AD, MP, and MV. The selection of an appropriate value for the number of clusters (k) is crucial in K-means clustering, and the "elbow method" is commonly employed to determine the optimal value of k. Due to the limitation of the number of fabrics in the database, it is necessary to determine the ideal number of clusters. By using elbow method, we found that k=6 is the optimal choice (the elbow of the curve). In addition, we applied Principle Component Analysis (PCA) to reduce the data of high dimensions to a plan before applying K-means. Then, the selected digital fabrics are clustered into different k groups (6 clusters), as demonstrated in Figure 3. After the clustering, the closest group of digital fabrics can be obtained by comparing the distance between the centroid of each cluster with the real fabric base on its estimated drape parameters.

2.4 Prediction Process

The main concept behind the prediction process is to analyze the characteristics of both real fabric (based on its drape parameter - calculated in Section 2.2) and the digital fabrics in the closest cluster derived in Section 2.3 (they are taken as leaning data for prediction), in order to identify the most similar fabric existing in the digital software database. The prediction task is carried out using the Min Euclidean Distance technique and five machine learning techniques based on the previous learning data, including K-Nearest Neighbors (KNN) [10], Random Forests [11], Naive Bayes [12], and Decision Tree [13] based on drape parameters, as shown in Figure 5. The results achieved include the name of the predicted fabric and its mechanical properties.

3 Results

The process of testing a real fabric (collected from our partners) is illustrated in Figure 4. Five machine learning models are applied to predict the results. It should be noted that the achieved results (predicted numbers of digital fabrics) may differ in some cases. In such cases, we can provide all the results and the users can decide by themselves which one is the most relevant according to their preference or experience. If the user's experience is not available, the majority rule can also be used to select the most relevant digital fabric. For example, if five learning models deliver the fabric n°90 and another n°95, we will naturally take n°90 as the most relevant fabric.
The achieved results may be affected by differences in the distance between the camera and fabric, as well as variations in the size of the image captured. These factors can influence the accuracy and consistency of the obtained results and should be taken into consideration when analyzing the data. In Figure 2.4, the drape parameters of the digital and real fabrics are different but their contour shapes are almost the same. We consider that they are very similar fabric samples. Our objective is to find the most similar fabric in the software database, and we can enhance our performance by extending the size of the database sample.

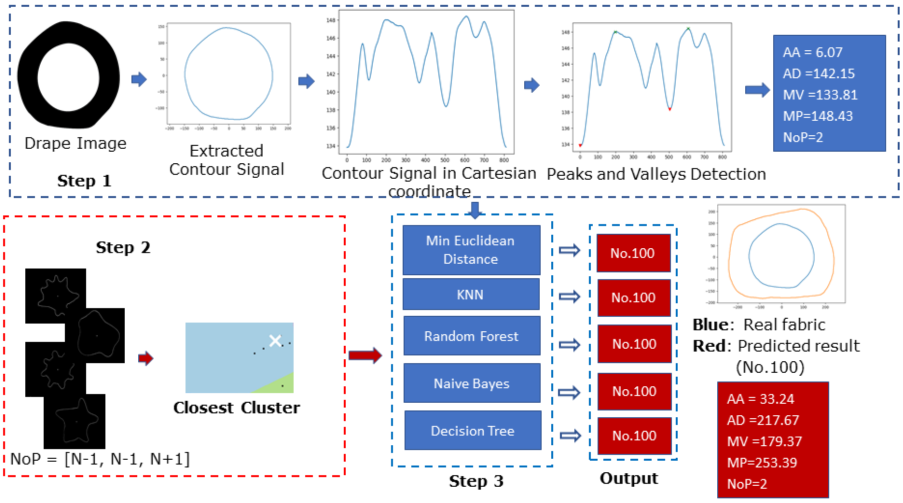

FIGURE 4 – *Testing in a real fabric*

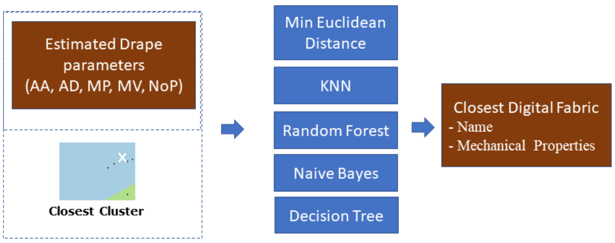

FIGURE 5 – *The process of Predicting the closest fabric based on Classification models*

4 Conclusion

The process of digitizing fabric can be accomplished manually, although it is important to acknowledge that this approach is inherently subjective and reliant upon the opponent of user/designer. With the objective of establishing a more precise and consistent approach, we initially developed an objective method to digitalize the digital fabric that most closely resembles the real fabric from the software database. Our objective is to identify the most accurate digital match for a given fabric within the software database. Our effort is try to find the best possible digital match for a given fabric within the software database. This process can be refined further to attain even greater accuracy. Further expansion of the digital fabric collection in the software database could potentially enhance the accuracy of our method.

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