Virtual Fitting: Real-Time Garment Simulation for Online Shopping
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Abstract
Without physically trying on a garment, online clothing shoppers are unable to decide the best size or color, and therefore are more likely to purchase clothes that do not fit. A solution to this online fit problem is virtual fitting. Using 3D modeling to help customers visualize how garments look on them requires garment simulation in real time. This paper proposes an innovative approach that utilizes machine learning to meet this real-time requirement and can be applied to virtual fitting systems.

Keywords: real-time garment simulation, virtual fitting, machine learning, physically-based simulation

1. Introduction
To assist online garment shoppers to choose the best fit, we want to simulate how a garment deforms according to the user’s body shape in a fast and accurate manner. Physically Based Simulation (PBS) has been the major technique to authentically simulate garment deformation based on the garment’s physical properties. However, PBS is a compute-intensive process that cannot well serve the needs of real-time applications. We propose an innovative way based on PBS to keep a certain degree of accuracy, and to integrate statistical methods such as neural machine learning to significantly speed up the simulation.

For each garment size, we learn a mathematical deformation rule that characterizes how the garment physically deforms on body models with different body shapes. Given any arbitrary body shape, garment simulation can be easily, instantly and accurately computed using the learned deformation rule. In a virtual fitting system that uses our method, a customer will input her customized body model and the system will simulate how a selected garment deforms on the body model realistically and in real time.

This paper consists of the following sections. Section 2 discusses the related work, section 3 explains our method and implementation in detail, section 4 presents our experimental results and we summarize the results in section 5.

2. Related Work
Cordier and Magnenat-Thalmann [1] use a data-driven approach to achieve real-time garment simulation. In pre-processing stage, their method generates a coarse mesh and calculates interpolators of coarse mesh deformation and wrinkle deformation separately. Runtime simulation includes deformation and refinement of the coarse mesh using the interpolators.

DRAPE [1] is one of the first research groups to introduce learning into computer animation and to learn models of cloth dynamics. The learned models can be used to dress body models in real-time with a garment customized to fit. DRAPE automatically reshapes a garment and deforms it to fit any body model. However, since clothes are not infinitely sized and customers do not always want the size that fits them best, DRAPE may not be appropriate for virtual fitting.
3. Method

Unlike DRAPE, our method dresses a garment on any body model without reshaping the garment. For a particular garment, we use PBS to simulate garment deformation on a set of training body models and we apply learning to derive the garment’s deformation rule. As a result, customers can visualize how a garment of any size (e.g. small, medium or large) will look on them.

3.1. Dataset Construction

Our body dataset consists of roughly 70 training and 10 testing body shapes of Asian females, with small-, medium-, and large-sized bodies equally distributed. Given a 2D pattern of a garment, we build our garment dataset by conducting PBS on each of the training bodies, which returns us 70 deformed garments. All the 3D bodies and garments are represented by triangular meshes. To reduce the high dimensionality of the 3D objects, we perform Principal Component Analysis on each of the objects to extract a reduced data subspace. We extract 20 principal components from each body and 10 principal components from each garment. In this way, our machine learning algorithm learns the mapping between a 70-by-20 body matrix and a 70-by-10 deformed garment matrix.

3.2. Neural Machine Learning

We implement a 2-layer (single hidden layer), fully connected, feed-forward backpropagation network to learn the general deformation rule. The converged weights of the two layers (input to hidden layer and hidden to output layer) store the deformation rule that maps the body input to the deformed garment output. Each specific garment has its own learned deformation rule. In the testing phase, given any arbitrary body model, the learned deformation rule of the garment calculates how the garment deforms on the body.

3.3. Refinement

Our method provides plausible prediction of garment simulation on body shapes. However, interpenetration may occur when the learned garment is overlaid on the body (Figure 2). We referred to DRAPE to refine our learned garment by minimizing a weighted sum of 3 interpenetration error measures.
4. Experimental Results

In order to test our method, we created one extra-large T-shirt and one medium-sized dress, used our algorithm to compute the two garments’ deformation rules and applied the rules to 9 testing body models, with small-, medium-, and large bodies equally distributed. The T-shirt has around 35,000 vertices and the dress has 19,000 vertices.

4.1. Qualitative Evaluation:

Figure 3 shows the results of our method on some of the testing body models. The garments are deformed according to the body shapes underneath them (e.g. the garments and the bodies underneath them have the same contour). Moreover, the results are consistent between different types of garments. Both the T-shirt and the dress on the same body have the same contour as the body underneath them.

4.2. Quantitative Evaluation:

The run-time performance and other quantitative evaluations of our method are shown in Table 1. We implemented our method in MATLAB and ran the program on a 64-bit desktop machine with a 3.1 GHz Intel i7-3770S processor and 8.0 GB of memory. Since this is a learning-based method, there is also an up-front run-time cost for the learning phase. For each of the garments, we need to use PBS to simulate how the garment deforms on the 70 training body models, pre-process the resulting garment meshes, and run our algorithm on the training dataset.

<table>
<thead>
<tr>
<th>Quantitative Performance Evaluation</th>
<th>T-shirt</th>
<th>Dress</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time for Garment Simulation (sec)</td>
<td>0.015</td>
<td>0.004</td>
</tr>
<tr>
<td>Time for penetration removal (sec)</td>
<td>0.327</td>
<td>0.311</td>
</tr>
<tr>
<td>Position Error (mm)</td>
<td>5.6</td>
<td>0.99</td>
</tr>
<tr>
<td>Shape Error (mm)</td>
<td>13.7</td>
<td>2.20</td>
</tr>
</tbody>
</table>

Table 1: Error measures for learned garments

Besides run time, we also defined two error measures to compare our results quantitatively with PBS results to evaluate the performance of our method.
The first error measure is error of position. This error measure indicates how well the garment can be put in the proper position and calculates the distance between the highest points in the two results (PBS and our results) along the height.

\[ E_{\text{position}} = Z_i^{\text{ours}} - Z_i^{\text{PBS}} \]

where \( Z \) is the value in the height and the \( i^{th} \) vertex is the highest vertex in the garment.

The second error measure is error of shape. This error measure calculates the average of the Euclidean distance between each pair of points on the two results and is associated with the difference of the overall shape of the two results (PBS and our results).

\[ E_{\text{shape}} = \frac{1}{n} \sum_{i \in V} |V_i^{\text{ours}} - V_i^{\text{PBS}}| \]

where \( V \) is the set of vertices in the garment and \( n \) is the number of vertices.

5. Conclusion
An efficient garment simulation method is presented. Based on PBS to keep a certain degree of accuracy, the proposed method utilizes machine learning to simplify and speed up the garment simulation. The promising experimental results show that the proposed method can achieve garment simulation in real time. The method is also highly scalable and can extend to any type of garment. Our future work will focus on improving the accuracy of the learned garment deformation and extending to other body poses.

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7. References