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Learning Clothing Pressure Fields via Physics-based Simulations

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I. Introduction

Accurate estimation of clothing pressure on the human body is crucial to understand physical factors that influence clothing comfort. Such a prediction requires the capability of expressing contact pressure fields in terms of different body sizes and types as well as garment size and material properties. However, such contact scenarios are generally too complex to be modeled by analytical methods. Experimentation also has certain drawbacks since it does not provide information about internal stresses, and precise measurement of the contact pressure between a pair of curved soft bodies is difficult.

Computational techniques are promising alternatives to overcome the aforementioned challenges, and they have been previously used to simulate clothing pressure. For instance, Horiba et al. [1] recently used finite element analysis (FEA) to simulate the underwear-induced pressure fields on the human body. They also measured the pressure using sensors placed at certain positions and observed a good match with respect to the simulation results.

Despite their utility, the computational cost of simulation techniques typically grows exponentially with the increasing degrees of freedom in the models. Moreover, when contact of multiple bodies is involved, most numerical techniques suffer from further challenges such as significantly longer computation durations due to the need for time stepping and simulation failures due to instabilities. Hence, over the last two decades, there have been continued efforts to incorporate machine learning techniques into computational methods to improve efficiency and stability. For example, for the rapid prediction of stress distributions within human organs, Liang et al. [2] used deep learning to develop a fast and accurate metamodel replacing FEA.

The intricate anatomy of the human body may require elaborate computational models with several thousand degrees of freedom to capture the deformation mechanics accurately. Such large models inherently induce high computational costs and are likely to suffer from the aforementioned numerical issues. The proposed study aims to address this problem by developing a deformation model based on deep neural networks trained with simulation data. First, a parametric model generator is developed to automatically create body and garment models. Then, the generated models are fed to a physics-based simulator. After that, the developed framework is used to collect a large amount of data for systematic combinations of the input variables. Finally, the dataset is used to train a deep neural network that maps the input variables governing the body and garment properties to the output pressure field on the body. Upon successful completion of the project, we expect to achieve a very precise and efficient model capable of simulating various clothing scenarios. Such a tool has great potential to be utilized by researchers, engineers, and designers working in the haptics and fashion fields.

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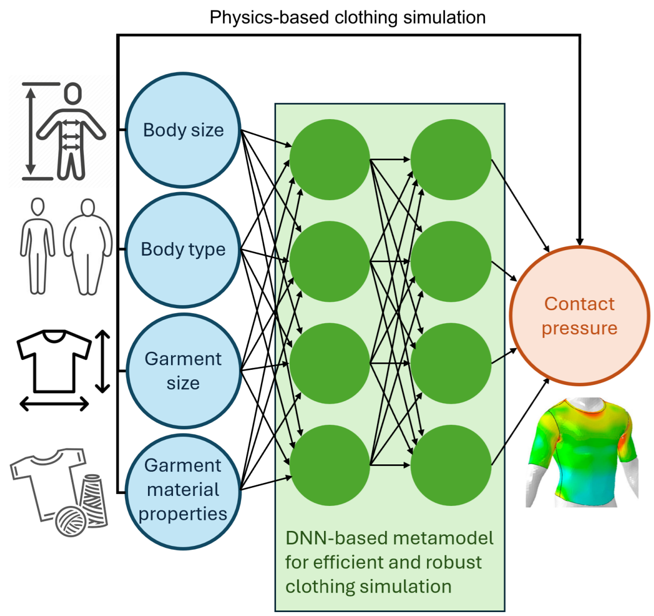

Fig. 1. Using a DNN-based metamodel to predict the clothing pressure for different body and garment properties.

II. Modeling and Data Generation

A. Body and cloth modeling

To attain realistic 3D human body models, we use the SMPL-X [3]. This tool is available as an add-on in Blender, which is a free and open-source 3D modeling program that we use to refine our meshes. We chose height, weight, and gender as the three main variables governing the body shape. For simplicity, we focus on the torso, which is automatically isolated from more complex body parts (head, forearms, and lower legs) using developed scripts (Fig. 2a).

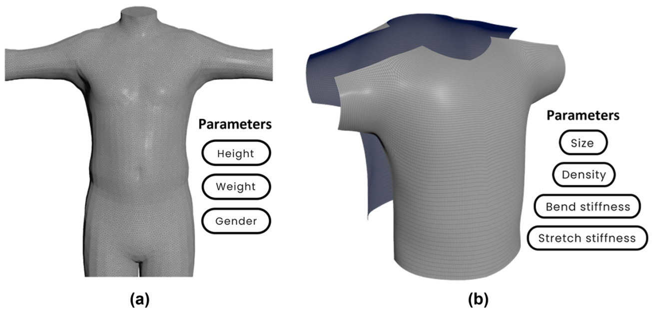

Fig. 2. 3D models used in clothing simulation: (a) Preprocessed and remeshed SMPL-X body model taking height, weight, and gender as parameters; (b) A sample t-shirt model generated by our in-house modeling tool which takes size, stretch stiffness, bend stiffness, and density as the input.

Coherent with our focus on the torso, we chose t-shirts as a simple type of cloth. We built our own parametric modeler, which is capable of generating t-shirt models for different sizes and materials. The specific properties that can be altered are selected as the size, stretch stiffness, bend stiffness, and density (Fig. 2b). For prevalent fabric types, the material properties typically cannot be altered independently. Thus, we chose four common types of fabric (cotton, silk, polyester, and wool) whose modeling properties have been reported for Houdini Vellum [4].

B. Clothing simulation

Once the body and garment models are created, their interaction needs to be analyzed. For this purpose, we use Houdini Vellum, which is a simulation framework relying on position-based dynamics (PBD). In PBD, particles representing the body and cloth are evaluated for deviations from their constraints due to external influences (e.g., collisions and gravity). Accordingly, particle positions are directly manipulated instead of using traditional force equilibrium calculations. This approach yields sufficiently realistic results with reasonable computational cost.

In the digital environment, making the cloth worn by the body requires specific strategies. We address this problem by cutting the t-shirt into half and virtually sewing back the two parts (Fig. 3a). With the initiation of contact, contact forces are applied on both cloth and body, causing them to deform until an equilibrium state is reached (Fig. 3b).

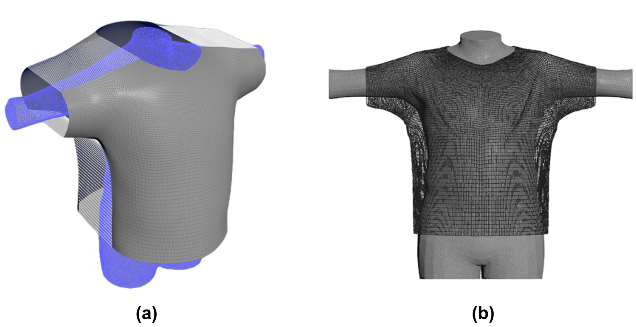

Fig. 3. Clothing simulation via PBD: (a) Virtual sewing operation for the t-shirt; (b) Deformed cloth and body meshes.

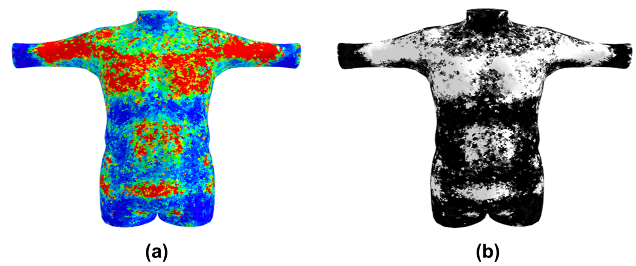

Fig. 4. Sample body stretch stress contours in (a) RGB and (b) black and white color scales.

C. Data processing

The Vellum framework is capable of providing stretch stress contours as RGB color values per node (Fig. 4a), where red and blue represent the highest and lowest values, respectively. We convert these contours into the black and white color scale (Fig. 4b) to obtain a single-channel distribution, which is more convenient to learn. To this end, we first normalize the RGB values to the [0 1] range. Then, we use the following formula to obtain the effective stress value (σ) at each node:

$$\sigma = \frac{R - B + 1}{2} \tag{1}$$

Here, R and B denote the red and blue values, respectively.

III. Outlook

We are currently testing simple neural networks including ResNet and DenseNet to learn the relationship between the input variables and output pressure field. Next, we will investigate more advanced DNN architectures such as transformers. We train distinct models for the male and female bodies to effectively learn the influence of height and weight, which are continuous variables. Once we validate the accuracy of the metamodels, we will provide them with a graphical user interface which will be published as open source. We will also explore different strategies reported in the literature to use the resulting pressure fields for comfort estimation. Ultimately, we aim to evaluate the comfort prediction capability of our models via user experiments.

References

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