A generalizable high-fidelity fabric simulation system optimised for e-commerce and design workflows

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ABSTRACT – REZUMAT

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Achieving high-fidelity, real-time garment simulation is a central challenge in virtual try-on systems. This difficulty stems from the need to balance accurate fabric-body interaction with strict computational constraints. This study presents a data-driven fabric simulation framework that integrates deformation learning with geometric refinement to enable precise fitting and photorealistic detail at interactive speeds. Compared with conventional physics-based solvers and simplified learning pipelines, the proposed approach achieves improved wrinkle fidelity, more stable fabric body correspondence, and higher computational efficiency without sacrificing visual quality. These results demonstrate the framework's practical viability for large-scale deployment in virtual try-on platforms, intelligent apparel design workflows, and digital retail visualisation applications. By unifying data-driven deformation learning with principled refinement strategies under a scalable computational paradigm, this work advances high-fidelity fabric simulation and provides a technical foundation for next-generation digital fitting, e-commerce platforms, and design workflows.

Keywords: *fabric simulation, learning model, virtual reality, wrinkle preservation, dataset*

Un sistem de simulare a materialelor textile de înaltă precizie, generalizabil, optimizat pentru comerțul electronic și fluxurile de lucru din domeniul proiectării

Obținerea unei simulări a articolelor vestimentare cu înaltă precizie și în timp real reprezintă o provocare centrală în sistemele de probare virtuală. Această dificultate decurge din necesitatea de a găsi un echilibru între interacțiunea fidelă dintre material textil și corp și constrângerile computaționale stricte. Prezentul studiu descrie un cadru de simulare a materialelor textile bazat pe date, care integrează învățarea deformărilor cu rafinarea geometrică pentru a permite o ajustare precisă și detalii fotorealiste la viteze interactive. În comparație cu soluțiile convenționale bazate pe fizică și cu fluxurile de învățare simplificate, abordarea propusă obține o fidelitate îmbunătățită a rezistenței la șifonare, o corespondență mai stabilă între materialul textil și corp și o eficiență computațională mai mare, fără a sacrifica calitatea vizuală. Aceste rezultate demonstrează viabilitatea practică a cadrului pentru implementarea la scară largă în platforme de probare virtuală, fluxuri de lucru inteligente de proiectare a îmbrăcămintei și aplicații de vizualizare digitală pentru comerțul cu amănuntul. Prin unificarea învățării bazate pe date a deformării cu strategiile de rafinare fundamentate, în cadrul unei paradigme computaționale scalabile, această lucrare aduce progrese în simularea materialelor textile de înaltă precizie și oferă o bază tehnică pentru probarea digitală de ultimă generație, platformele de comerț electronic și fluxurile de lucru de proiectare.

Cuvinte-cheie: *simularea materialelor textile, model de învățare, realitate virtuală, păstrarea rezistenței la șifonare, set de date*

INTRODUCTION

Accurate and efficient simulation of fabric behaviour remains a fundamental challenge for scalable virtual try-on systems. Existing approaches have achieved progress in either visual realism or physical accuracy, yet few methods simultaneously preserve fine fabric details, maintain robustness across diverse fabrics and body shapes, and meet real-time performance requirements. The objective of this study is to develop a unified learning-driven framework for fabric deformation. This framework aims to achieve high fidelity while maintaining interactive computational efficiency, enabling practical deployment in next-generation digital fitting systems. Early research relied on image-based techniques or handcrafted physical models to approximate fabric appearance. Recent deep learning approaches improved automation and adaptability. For example, convolutional networks have extracted geometric features from RGB-D data to guide fabric smoothing and flattening, but these methods require large-scale training data and show limited generalisation to diverse fabric properties [1]. Comprehensive reviews have documented the progression from two-dimensional image manipulation to three-dimensional-aware deep networks while emphasising persistent challenges in scalability and system robustness [2, 3]. Reinforcement learning has also been applied to robotic cloth manipulation with encouraging sim-to-real transfer, yet it depends on

extensive physical simulation and complex training pipelines [4]. From a complementary perspective, physics-informed approaches have focused on accurate material modelling. Mesoscale frameworks based on inverse parameter estimation capture yarn-scale interactions in UHMWPE fabrics [5], while unified hyperelastic models address nonlinear deformation behaviour to reduce wrinkling in woven prepregs [6]. Despite their accuracy, such methods remain computationally intensive and are generally unsuitable for interactive applications requiring real-time response. In addition, perceptual studies demonstrate ongoing difficulties in achieving visually natural fabric appearance under varying body shapes, motions, and lighting conditions [7]. Surveys of clothing simulation research further highlight fragmented methodologies and the absence of unified evaluation benchmarks, which continue to impede consistent assessment of fabric realism [8].

Building on these limitations, this study proposes a machine learning-driven virtual simulation framework that integrates data-driven mesh deformation with perceptually guided geometric refinement to achieve accurate fitting, realistic wrinkle reconstruction, and stable real-time performance. The proposed approach avoids simplified fabric geometry and handcrafted parameter tuning, offering a scalable solution for high-fidelity virtual fabric depiction across diverse application scenarios.

DATASET

A robust foundation for virtual fabric display and simulation was established using a structured dataset containing 38,913 2D and 6,350 3D samples. A graphic segmentation algorithm constructed temporal sequences, represented as a discrete time series. This time-conscious representation captures dynamic postures and supports 3D shape reconstruction while preserving realistic folds, providing the necessary foundation for modelling plausible draping (figure 1).



Fig. 1. Example of fabric dataset

An object's spatial pose requires six degrees of freedom: three translational variables (x, y, z) for position and three rotational variables (roll, pitch, yaw) for orientation. For rigid objects, pose is defined as a fixed transformation relative to a canonical origin. This definition fails for deformable objects like cloth. Their surface geometry varies continuously, making the rigid pose definition inapplicable [9]. This annotation scheme provides consistent spatial representation and precise geometry for learning tasks. Coupling fabric appearance with pose matrices enables supervised training, supporting generalisation across fabric types. If multiple instances (N) are present, N corresponding 4×4 matrices are generated to describe their spatial poses (figure 2).

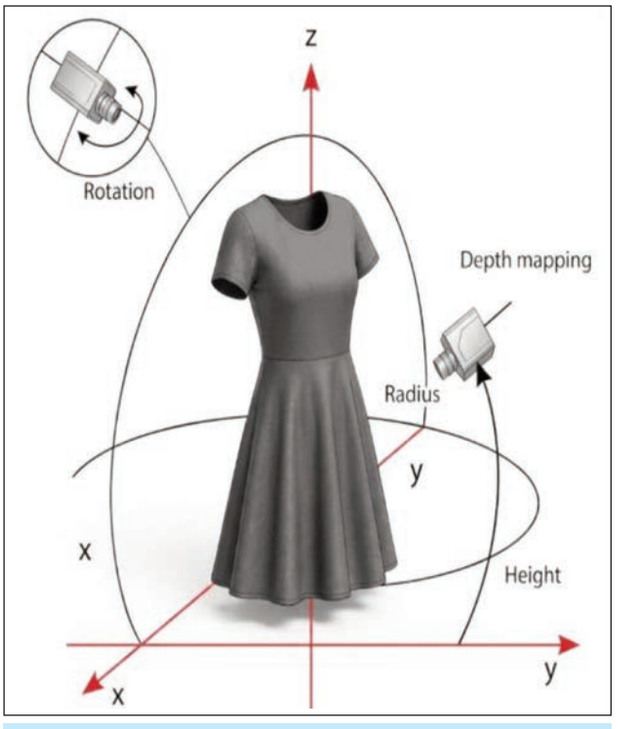


Fig. 2. Fabric depth mapping configuration

CLOTHING VIRTUAL DISPLAY NETWORK BASED ON DEEP LEARNING

By integrating human body and fabric datasets with a mathematical model for body reconstruction and a spatial perception-based fabric prediction scheme, this method achieves rapid generation of high-fidelity virtual fabric renderings [10]. The proposed framework, detailed in figure 3, utilises an encoder-decoder generator architecture. This system effectively captures depth maps and sequential data. It extracts distinct features from both the body and fabric inputs. Principal Component Analysis (PCA) then compresses these features into a shared latent space. Within this space, a fabric fitting regressor predicts vertex displacements. This prediction generates natural fabric deformations. To ensure structural coherence and preserve wrinkle dynamics, the skinning matrix is optimised. This optimization utilizes the reconstructed body geometry [11]. Using a data-driven pipeline,

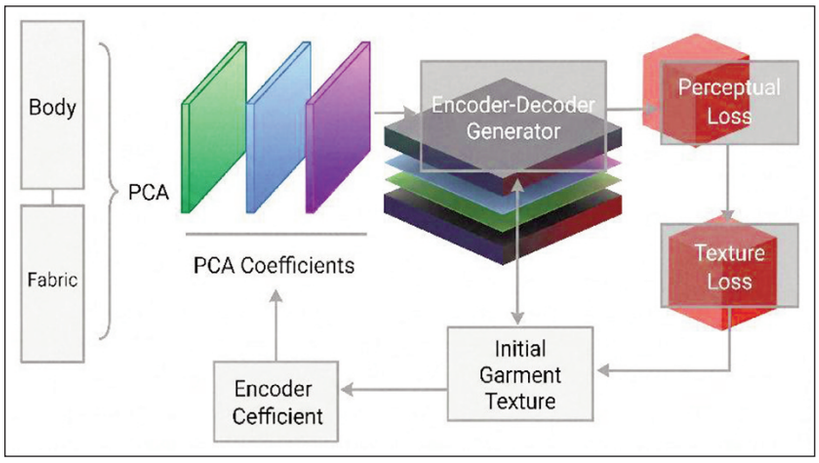


Fig. 3. Network framework of fabric virtual display

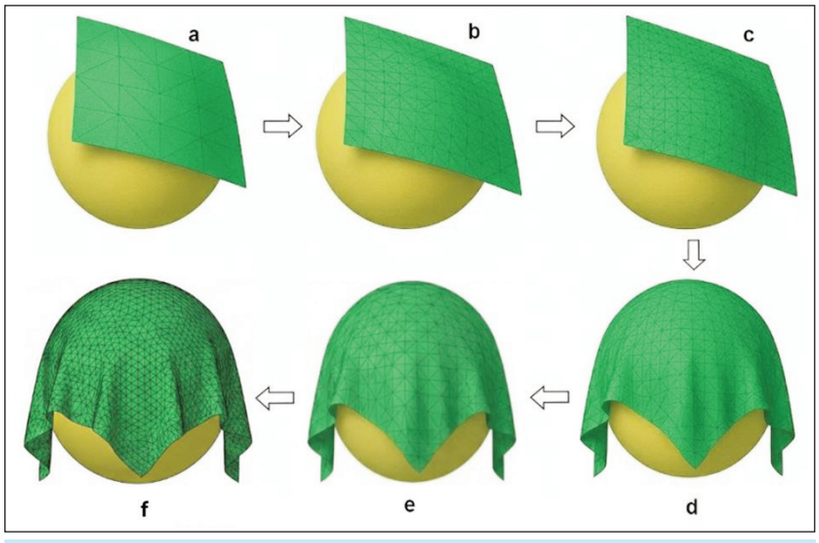


Fig. 4. Simulation of collision between fabric and spherical body approximations

the regressor couples body and fabric models by simulating collisions between the fabric mesh and spherical body approximations (figure 4), progressively displacing vertices from initial separation to full conformity. This process yields realistic wrinkle formation and a faithful virtual fabric display.

Specifically, a fabric virtual display network based on deep learning is composed of shape parameters θ. The deformable human mesh G_h and the deformable fabric mesh G_c on the human model are composed. Based on physical mechanics, $N_c(\theta)$ is the mechanical feedback result of the human fabric model in the virtual display of fabrics. Therefore, the equation of the human body model is as follows:

$$G_h(\theta) = S\{U_b(\theta),\theta,s_b\} \quad (1)$$

where $S(\cdot)$ is a skinning equation, $U_b(\theta) \in R^{3\times V_h}$ is a human body mesh template containing V_h vertices, and S_b is the skinning weight matrix. Similar to the human body model equation, the fabric model equation is as follows:

$$U_G(\theta) = U'_G + R_G(\theta) \quad (2)$$

Among them, $U'_G \in R^{3\times V_G}$ is a fabric mesh template containing V_G vertices, and R_G is a nonlinear regressor input as human shape parameters. The equation for generating fabric mesh deformation through skin equations is as follows:

$$G_c(\theta) = S\{U_c(\theta),\theta,s_c\} \quad (3)$$

Map the vertices of the fabric mesh template onto adjacent triangles, and combine them with S_b to obtain the skin weight matrix S_c.

Therefore, the virtual display of fabrics is achieved by learning the fabric fitting regression of the template, and the key to this process is to calculate the displacement of the fabric mesh. The working principle of the fabric fitting regression device is as follows:

$$R_G(\theta): R^{|\theta|} \rightarrow R^{3\times V_G} \quad (4)$$

By inputting body shape parameters θ, the displacement $\Delta D' \in R^{3\times V_G}$ of each vertex is generated, and the formula for fabric fitting regression is as follows:

$$\Delta D = \Psi(N_c(\theta)) - U_G \quad (5)$$

$\Psi(\cdot)$ is a clothing fitting tool, which maintains smooth deformation of the fabric and uses a multi-layer neural network to minimise the loss function as follows:

$$L = \sum_{i=1}^{k} \left\| [\Psi(N_c(\theta)) - U_G] - R_G(\theta) \right\|_2^2 \quad (6)$$

The fabric mesh exhibits stretching and draping deformations in response to body changes. This behaviour is regulated by a fabric fitting regressor that optimises vertex fields subject to global similarity constraints [12]. By optimising mesh displacements, the proposed framework generates realistic fabric wrinkles with adaptive subdivision for surface refinement. The model is trained end-to-end using a convolutional neural network (CNN) that maps a template mesh to deformed fabric vertices. Supervision combines loss terms on vertex positions and surface normals, together with an energy constraint to prevent interpenetration while preserving wrinkle details. Boundary artefacts are mitigated using a Gaussian mixture prior and Graph Cuts on a uniformly segmented template. The network takes 64×64×3 depth maps as input and outputs fabric meshes in either full or PCA-compressed form. Convolutional blocks with ReLU activations and dropout efficiently predict vertex displacements, enabling a fast and high-quality virtual fitting pipeline.

EVALUATION OF CLOTHING VIRTUAL DISPLAY BASED ON DEEP LEARNING

The network balances visual quality and efficiency. A multilayer model predicts fabric shape and pose using a fit regressor with up to 1,200 hidden neurons. A 15% dropout rate mitigates overfitting with an initial learning rate of 0.0001. Training uses 300 sequences and 50 test sequences covering 16 body shapes. Truncated BPTT with a 100-step limit reduces computation, while shape interpolation and vertex displacement yield realistic deformations.

QUANTITATIVE EVALUATION

The non-linear clothing vertex regressor increases per-frame mesh deformation time from 6.31 milliseconds for 4710 meshes to 10.91 milliseconds for 15210 meshes, demonstrating low computational complexity and suitability for interactive use, as shown in table 1.

Memory usage remains compact, with clothing fit regression requiring about 1.1 megabytes and wrinkle regression about 108.1 megabytes, supporting efficient fabric simulation in real-time environments.

Table 1

FABRIC DEFORMATION TREATMENT TIME		
Triangle count	**Mean (ms)**	**Standard deviation**
4710	6.31	0.28
7710	8.23	0.30
15210	10.91	0.31

Multiple linear regression models are evaluated during training to assess fitting performance. A linear skinning algorithm aligns the clothing mesh with the human body model. Iterative optimisation allows the Multi-Layer Perceptron (MLP) network to produce smooth hierarchical simulation results. These accurately represent diverse body shapes and fabric forms. To quantify strain constraints, the average vertex error is computed for each body vertex. The proposed MLP achieves accurate and stable fitting performance. Low-level displacement constraints guide the regressor during deformation. This ensures natural fit and realistic wrinkles. Implicitly learning body fabric contact reduces physical simulation limitations. Vertex position error provides a reliable generalisation metric for evaluation.

QUALITATIVE EVALUATION

The fabric achieves smooth chest-to-abdomen fitting with natural hem drape, and fine wrinkles are generated from 128 × 128 px inputs through a CNN regressor trained on collision-free datasets with displacement constraints, as shown in figure 5, *a*. Wrinkle transitions progress from slight mesh deformation to pronounced waist creases while maintaining hem curvature and precise alignment to spine and shoulders, as shown in figure 5, *b*. The hem shifts dynamically from an initial ~90° suspension to a thigh-conforming bend, preserving drape stability under motion, as shown in figure 5, *c*.

The two level regression separates body shape fitting from nonlinear dynamic responses, enabling over 200 fps real-time virtual try-on, as shown in figure 5. Enhanced Lagrangian strain constraints maintain stability on irregular meshes exceeding 50 k vertices, delivering physically plausible, high-detail deformation without the computational cost of full physics-based solvers. Fabric adapts naturally to motion with physical realism. Enhanced Lagrangian strain constraints keep large irregular meshes stable and ensure great detail in fabric motion under complex movements.

DISCUSSION

The proposed method was subjected to a rigorous evaluation protocol, incorporating five-fold cross-validation and leave-one-shape-out experiments to ensure robust generalisation. Across diverse fabric categories, the model demonstrated highly stable generalisation, achieving a consistent mean vertex error of 8.25 mm. This geometric accuracy is competitive with methods such as TailorNet, which typically exhibits an error range of 10–12 mm. Crucially, the approach achieves real-time performance, operating at 6–11 ms per frame, exceeding 200 fps.

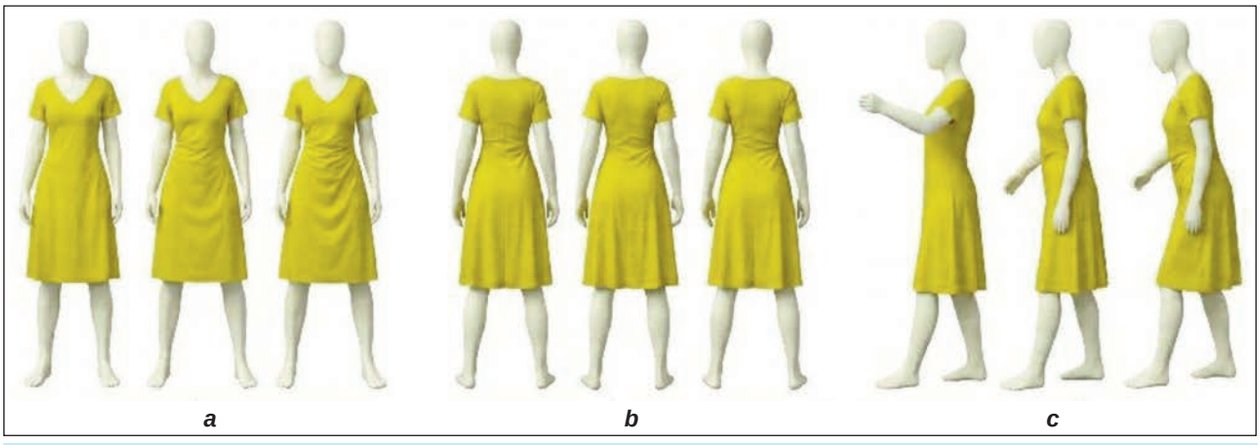


Fig. 5. Virtual display of clothing on the *a* – front, *b* – back, and *c* – sides

Table 2

COMPARISON OF FABRIC SIMULATION METHODS			
Method	**Mean Vertex Error (mm)**	**Wrinkle fidelity**	**Runtime**
Proposed method	8.25	High	6–11 ms
DeepWrinkles	9–11	High	13 ms
TailorNet	10–12	High	1–2 ms
GarNet	9–10	Moderate–High	100× faster than PBS

While TailorNet offers lower latency of 1–2 ms, the proposed method provides superior performance compared to DeepWrinkles 13 ms [13,14].

Furthermore, the method was qualitatively confirmed to offer superior wrinkle preservation, rated as high fidelity. This high fidelity result is significant because the method maintains efficiency without sacrificing visual quality, unlike GarNet, which offers only 'Moderate-High' fidelity [15]. Direct numerical comparisons must be interpreted cautiously due to known variations in experimental protocols across different studies. Future work will focus on establishing standardised benchmarking protocols and incorporating a broader spectrum of fabric properties to enhance physical realism.

CONCLUSIONS

The high-fidelity framework achieves accurate fabric interaction. It ensures fine wrinkle preservation and sustains real-time performance over 200 FPS. Quantitative results show lower vertex errors and improved efficiency compared with other methods. This confirms robust generalisation across diverse body shapes. The framework offers significant industrial relevance for e-commerce platforms and design workflows. It provides a photorealistic virtual try-on experience. This strategy significantly curbs product return rates while simultaneously advancing global sustainability goals. Limitations remain in generalising to unseen fabric properties. Temporal coherence under complex motion must be ensured. Future work focuses on unified benchmarking protocols. Training will extend to a broader range of fabric properties.

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