Journal of Applied Automation Technologies

Research Paper

Neural Radiance Fields (NeRF) for Dynamic Lighting Effects and Real-Time Rendering Optimization in Virtual Fashion Show Garment Design

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Abstract. Due to the presence of many physical fashion stores and virtual fashion exhibitions on the internet, virtual clothing research is becoming increasingly common. Rendering fabrics with photorealistic quality under dynamic lighting and its practical application remain the main obstacles that must be overcome. Based on the new technology of neural radiance fields, a method for real-time digital rendering of very delicate clothing is proposed. By encoding the characteristics of clothing materials through a special network structure, and then using dynamic lighting techniques to achieve precise rendering of appearance and fabric light response. A more optimized real-time rendering pipeline, using GPU acceleration and adaptive sampling techniques, ensures smooth operation of clothing in terms of image quality. Based on various environmental lighting and dynamic changes in similar clothing, as well as a complete dataset containing real and hypothetical clothing items. Compared to traditional physics-based rendering methods and previous neural rendering methods, it improves image clarity, structural consistency, and perceptual effects. Based on this paper, the framework can support interactive e-commerce, digital fashion design, and virtual fitting programs. In the future, various complex textiles and lighting variations will be added. Provide a reliable and scalable system design to achieve the visualization of high-quality digital garment images.

Keywords: *Neural Rendering, Dynamic Lighting, Real-Time Visualization, Garment Simulation, Deep Learning, Virtual Reality, Image Synthesis*

Received on 29 November2025, Accepted on 24 February 2026, Published on 03 March 2026

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Introduction

In the fields of computer graphics, computer vision, and virtual reality, realistic digital clothing visualization has recently become increasingly popular [1]. With the development of virtual fashion shows and online clothing platforms, the demand for realistic fabric simulation and real-time rendering of dynamic lighting environments is continuously increasing [2]. The physically-based rendering (PBR) technology used for fabric simulation in clothing visualization has made significant progress, but the generated images often appear somewhat dull and sluggish [3]. With the emergence of large-scale deep learning frameworks and neural rendering technologies, many methods for creating virtual environments that combine 3D views and appearance information have emerged [4]. NeRF provides a new perspective and exceptionally high performance for generating static 3D models [5]. Another reason is that with the development and popularization of the fashion industry, establishing a "presence" in real life has become increasingly important [6]. The improved rendering mode can use multiple light sources to simulate outdoor scenes and display rich details on the clothing. In addition, it also supports real-time interaction [7]. Many interdisciplinary studies have provided foundational algorithms and experimental results for this field [8].

Neural implicit representations have made significant progress in scene representation, but they cannot effectively render scenes [9]. Simple NeRF models cannot be directly used for real-time and interactive scenes because their computation speed is too slow [10]. Secondly, existing systems based on NeRF cannot fully understand the characteristics of real fabrics with anisotropic reflection and nonlinear light scattering properties,

https://doi.org/10.64972/jaat.2026v4.120p139-151

making them far from the actual situation [11]. The system's inability to simulate dynamic lighting conditions is another issue. However, this is crucial for a convincing virtual fashion show environment and has not yet been fully researched [12]. New technologies currently cannot fully meet the demands of dynamic lighting changes and complex garments in virtual fashion scenes [13]. Moreover, many neural rendering acceleration methods only target ordinary objects and do not address the specific needs of the frequent high-frequency details of digital clothing [14]. Resolving the aforementioned complex relationships and achieving efficient interaction between dynamically lit garments is a research hotspot in the field of digital fashion technology [15].

Based on the aforementioned reasons, this paper proposes a novel method that applies Neural Radiance Fields (NeRF) to real-time high-precision 3D reconstruction and dynamic light effect simulation. This will meet the needs of virtual fashion shows. We proposed an improved network architecture that can more accurately simulate the complex fabric characteristics and photon responses under various lighting conditions. At the same time, to ensure the smooth operation and interaction with demand-based virtual runway environments, a high-performance rendering pipeline was designed, utilizing network and GPU upgrades. In addition, the latest methods were compared with those that have implementation capabilities and low computational intensity constraints. The main results are as follows: (1) A NeRF model for clothing, designed to render expressive appearances under dynamic lighting; (2) A real-time GPU-optimized rendering framework for virtual fashion show applications; and (3) In-depth research to emphasize the authenticity, response time, and applicability in the future development of the digital fashion industry.

Related Work

Neural Rendering Techniques

By directly using deep neural network models to simulate light scattering and other effects in the scene, such high-fidelity rendering can be achieved [16]. Neural rendering typically uses volumetric or implicit field representations. This method is more flexible than traditional geometry-based rendering pipelines when used alone and has many applications [17]. The initial demonstration of Neural Radiance Fields (NeRF) achieved satisfactory results in visualizing complex static scene volumes using multilayer perceptrons [18]. Nonlinear transformations enhance NeRF. Continuous transformation from spatial coordinates to view direction, simultaneously rendering color and density.

Since then, neural volumetric rendering technology has improved in scalability, efficiency, and the generation of dynamic scenes. Using multi-scale methods, mips-neerf and its variants can achieve near real-time interaction by reducing sampling aliasing and memory consumption [19]. To address external light attenuation and partial occlusion, some extended neural field methods such as NeRF-W and masked-NeRF [20]. Digital clothing displays have recently studied neural relighting methods, altering the ambient light distribution through post-processing [21]. Technologies such as tensorized neural field theory and Instant NGP have been developed to achieve hardware-accelerated real-time versions [22]. According to previous research, neural rendering technology has become a necessary method for generating more realistic and higher resolution images. Therefore, applications related to this will be developed in the field of virtual clothing displays [23].

Traditional Garment Rendering Approaches

Traditional garment rendering and simulation techniques have a long history and are very important in modern academic and commercial fields [24]. By using complex mathematics to achieve physically-based rendering of clothing reflection effects, these mathematical models include transparency, diffuse reflection at different scales, and light scattering within the fabric [25]. To accurately simulate the motion and folding process of fabrics, particle-based, mass-spring, and finite element methods are used to reconstruct mechanical deformations caused by various external forces. Physics-based methods are accurate, reliable, and flexible, but they have high computational costs, especially in applications requiring real-time operation or detailed visual effects, making them relatively expensive [26].

The introduction of hybrid rendering frameworks can improve the realism of virtual clothes in Digital Goods. Uses high-performance shading Systems and Geometry-based simulation technology. For instance, using BRDFs, spherical harmonics and sub-surface-scattering models to render a more realistic appearance of different types

https://doi.org/10.64972/jaat.2026v4.120p139-151

of fabrics, including glossy silks and irregular wools [27]. Although there has been some improvement, in terms of application for large-scale Data-driven interaction-based Digital Fashion Platforms, it still requires substantial amounts of manpower-intensive operation at its core. The combination of machine learning for automatic processing and neuro-perception-inspired renderings is expected to improve the Quality, adaptation ability of Clothing visualisation [28].

Limitations in Current Virtual Fashion Shows

Virtual fashion shows are a new direction of development for the industry; however, there is still an issue with digital clothing visualisation pipelines that restricts wide-ranging use and users' experiences [29]. The display of graphic quality and response speed are inconsistent. Traditional physics-based models and shallow learning methods cannot effectively handle complex scenes or rapidly changing viewpoints on GPUs. Delays and other issues may occur. Another issue is the inability to simulate the complex optical properties of highly technical fabrics. For example, in dynamic multi-light source situations often encountered on the runway, anisotropy and reflectivity depend on the microstructure [30]. Today's clothing cannot be directly touched by consumers, and its sensitivity to simulated fabric and light response may affect consumers' perception and appreciation of brand style and product information, weakening the company's brand effect.

In addition, many of the existing digital fashion show interactive systems are not easy to use in different network environments, Platforms, and Devices. Many of the systems cannot fully satisfy users' demand for interactive functions, including immediate response to changes in clothes, animations, and user settings. They cannot stimulate innovation and promote application in the market. Also due to a cumbersome, lengthy access control system, it has poor scalability and automated features for digital-fashions-related content creation. To satisfy the new requirements of high-precision interactive digital fashion, we need to make breakthroughs in neural rendering, real-time signal processing and material appearance model synthesi.

Methodology

Enhanced NeRF Model for Garment Representation

An improved method is proposed, which uses NeRF technology to display rich textures and interactive effects of digital clothing in real-world scenes. The system consists of three parts, as shown in Figure 1 below: a clothing-aware NeRF backend network, a dynamic lighting addition module, and a real-time rendering engine. Under complex lighting conditions, this architecture can reconstruct the entire clothing scene. The scene also supports high-fidelity inference for virtual fashion interactions.

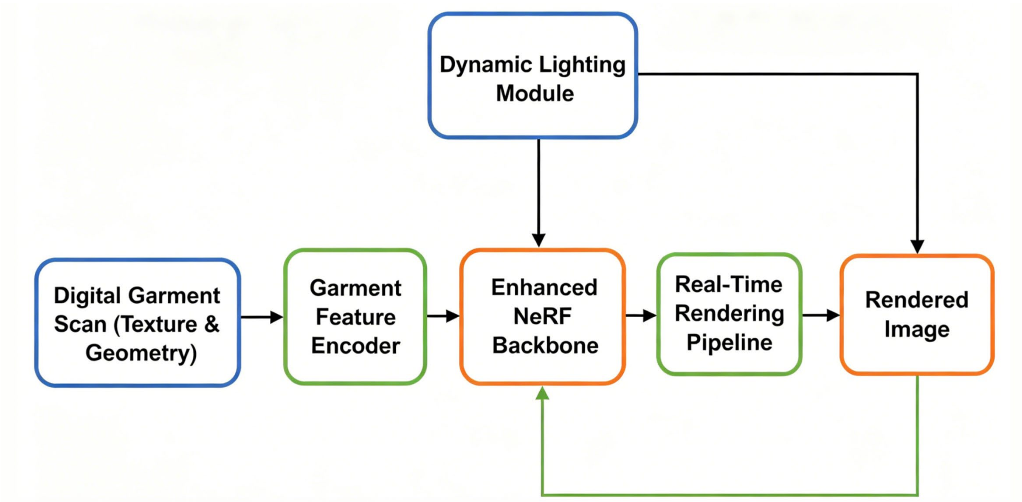

Figure 1. High-level architecture of the proposed NeRF-driven garment rendering system

In this architecture, the core function maps the 3D query position $\mathbf{x} \in \mathbb{R}^3$, viewing direction $\mathbf{d} \in \mathbb{R}^3$, and a latent garment descriptor $\mathbf{m} \in \mathbb{R}^k$ to radiance color and volume density:

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$$(\mathbf{c}, \sigma) = F_\Theta(\mathbf{x}, \mathbf{d}, \mathbf{m}) \quad \text{Eq.(1)}$$

where Θ are trainable parameters, $\mathbf{c}$ is color, and σ is the volume density. The clothing descriptor $\mathbf{m}$ extracts the fundamental fiber, weave, and surface characteristics of fabric or fabric images by encoding a compact neural network. Therefore, the network makes predictions based on the specific optical properties of the fabric (gloss, anisotropy, and specular highlights).

Use high-frequency trigonometric basis functions to encode positions and encode coordinates:

$$\gamma(\mathbf{x}) = [\sin(2^0\pi\mathbf{x}), \cos(2^0\pi\mathbf{x}), \ldots, \sin(2^{L-1}\pi\mathbf{x}), \cos(2^{L-1}\pi\mathbf{x})] \quad \text{Eq.(2)}$$

Combining positional encoding with latent garment encoding, it is passed through a multilayer perceptron, which includes skip connection layers and dropout regularization. The attention mechanism is used to focus on areas where embroidery patterns, stitching lines, or changes in color and texture frequently occur.

For every pixel in each training view, a camera ray is sent from inside the garment volume and divided into N points. Ray tracing to compute the radiance on a given ray $\mathbf{r}$:

$$\hat{C}(\mathbf{r}) = \sum_{j=1}^{N} T_j\left(1 - e^{-\sigma_j\delta_j}\right)\mathbf{c}_j \quad \text{Eq.(3)}$$

where transmittance $T_j = \exp\left(-\sum_{k=1}^{j-1} \sigma_k\delta_k\right)$ and δ_j is the segment length.

Reconstruction Loss serves as the first-order optimisation target:

$$\mathcal{L}_{\text{recon}} = \frac{1}{|\mathcal{R}|}\sum_{\mathbf{r}\in\mathcal{R}} \left\|\hat{C}(\mathbf{r}) - I_{\text{gt}}(\mathbf{r})\right\|^2 \quad \text{Eq.(4)}$$

where I_{gt} is the ground-truth color at pixel $\mathbf{r}$.

We further impose a perceptual texture loss using a pretrained textile feature extractor:

$$\mathcal{L}_{\text{perc}} = \frac{1}{|\mathcal{R}|}\sum_{\mathbf{r}\in\mathcal{R}} \left\|\phi(\hat{C}(\mathbf{r})) - \phi\left(I_{\text{gt}}(\mathbf{r})\right)\right\|^2 \quad \text{Eq.(5)}$$

Also add a density-regularisation term to constrain volume:

$$\mathcal{L}_{\text{reg}} = \frac{1}{|\mathcal{R}|}\sum_{\mathbf{r}\in\mathcal{R}} \sum_{j=1}^{N} |\sigma_j| \quad \text{Eq.(6)}$$

In terms of targets:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{recon}} + \alpha\mathcal{L}_{\text{perc}} + \beta\mathcal{L}_{\text{reg}} \quad \text{Eq.(7)}$$

Tunable hyper-parameters α, β through validation.

Parameterization of view-dependent garment effect via Spherical Harmonics:

$$\mathbf{c} = \sum_{l=0}^{L} \sum_{m=-l}^{l} Y_l^m(\mathbf{d}) w_l^m(\mathbf{x}, \mathbf{m}) \quad \text{Eq.(8)}$$

where Y_l^m are basis functions and w_l^m are output weights.

Training leverages a hybrid dataset of real and simulated textile scans with controlled and variable lighting. Data augmentation, strata division sampling and validate generalise clothes type and run ways light condition.

Optimized Dynamic Lighting Simulation

In virtual fashion, the realism of clothing requires simulating changes in stage lighting and ambient light. Figure 2 shows the interaction process between the lighting simulation module and real-time rendering. We will describe lighting as a low-dimensional vector that changes over time and add it to the NeRF input. Therefore, the incident light field and the hidden clothing encoding determine the radiance intensity at each point.

Below is the ambient lighting model for surface position $\mathbf{x}$ and normal $\mathbf{n}$:

$$L_{\text{env}}(\mathbf{x}, \mathbf{n}, t) = \sum_{i=1}^{S} l_i(t) f_i(\mathbf{x}, \mathbf{n}) \qquad \text{Eq.(9)}$$

Each element corresponds to a virtual position, wash or background light at different times t.

An illumination modulation signal is input into the central NERF network to generate the instantaneous appearance of spotlights, moving stage objects, and color vortices. To integrate direct and indirect lighting, the neural SVBRDF estimator also estimates the spatially varying reflectance properties:

$$F_{\Theta}(\mathbf{x}, \mathbf{d}, \mathbf{m}, \ell(t)) \qquad \text{Eq.(10)}$$

The final radiance at each sample is the sum of direct and neural-predicted indirect contributions:

$$\mathbf{c}_{\text{tot}} = \mathbf{c}_{\text{dir}} + \gamma \mathbf{c}_{\text{indir}} \qquad \text{Eq.(11)}$$

Where γ is material-dependent.

Animated lightning adds a time-continuous smoothness term to the simulation of realistic lightening.

$$\mathcal{L}_{\text{temp}} = \frac{1}{T-1} \sum_{t=1}^{T-1} \sum_{i=1}^{N} \left\| \mathbf{c}_i^{(t+1)} - \mathbf{c}_i^{(t)} \right\|^2 \qquad \text{Eq.(12)}$$

Finally, supervision integrated photometric loss and temporal loss to ensure the stability and fidelity of dynamic lighting.

The lighting training samples come from high-fidelity synthetic scenes and controlled recording environments of real scenes. In digital programs, seemingly realistic and imaginative lighting scenes are often used for effective learning.

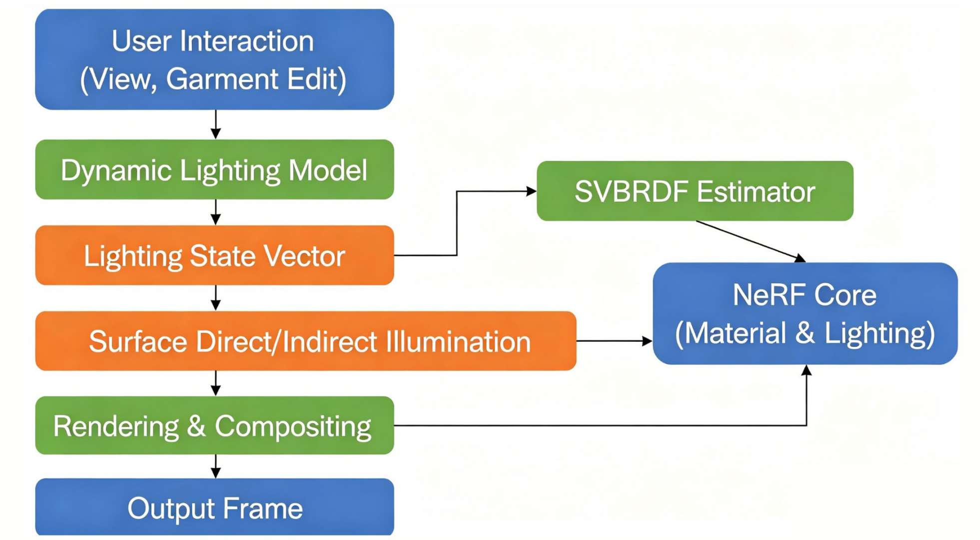

Figure 2. Dynamic Lighting and Real-Time Rendering Workflow

Real-Time Rendering Pipeline

We provide an efficient, low-latency, high-precision real-time rendering system to meet the strong demand for virtual clothing interaction. In this process, the integration of neural volumetric rendering and traditional graphics hardware acceleration performs excellently when run separately.

During initialization, the mesh of the 3D clothing, neural material code, and parametric light sources are loaded into the GPU memory for quick access, while reducing runtime costs. Each rendering will render a full screen, regardless of the camera position, with all rays being cast simultaneously onto this plane. The system will batch query the spatial coordinates, direction vectors, clothing encoding descriptors, and lighting information for each

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ray. In order to evaluate these queries, a specially designed multilayer perceptron network has been optimized for the use of GPU tensor cores. The network also supports mixed-precision arithmetic operations. This design can achieve prediction accuracy, numerical stability, and high throughput performance.

Each pixel's colour is the result of a combination through volumetric rendering, as follows:

$$\hat{C}(\mathbf{r}) = \sum_{j=1}^{K} T_j \left(1 - \exp\left(-\sigma_j \delta_j\right)\right) \mathbf{c}_j \quad \text{Eq.(13)}$$

Light passes through ($\mathbf{x}_j, \mathbf{d}_j, \mathbf{m}_j, \ell_j$) to obtain local geometric information, directional cues, modern lighting, and fabric material characteristics. A multi-layered design that allows for the reconstruction of various appearance details across multiple frames, such as intricate patterns and different highlights.

The computational load is adaptive based on the data. Display visually prominent areas at points with higher sampling density, such as areas under clothing contours or lighting points. Using temporally consistent sparse representations and hash-based lookup tables, the number of neural network calls per image is reduced. This balance achieves reasonable acceleration and brings it closer to photo-realistic details.

The scheduling of the thread pool mechanism can control the rendering throughput to maximize resource utilization. Efficiently allocate time to complete frames at each stage:

$$T_{\text{frame}} = \max(T_{\text{raster}}, T_{\text{NeRF}}) \quad \text{Eq.(14)}$$

T_{raster} includes the classic GPU rasterisation process, such as depth buffering and occlusion test; And T_{NeRF} contains neural volume evaluation and colour composition. To prevent both the neural and rasterisation stages from becoming system bottlenecks during operation to maintain good real-time performance for changes in scenes or users' actions quickly.

In order to achieve reliable interaction results across different hardware environments and scene variations, a simplified distilled neural "student" model was adopted. The model can approximate the output values of the main network, rather than being an exact clone. A lightweight alternative model can be flexibly invoked in low-computation-sensitive areas or secondary views to maintain continuous interaction in virtual reality experiments and large-scale live streaming applications.

Asynchronous prefetching ensures responsiveness. Adjustments to viewpoint, lighting, and clothing attributes will be made according to user requirements, generating quick or medium preview images from cached features or interleaved outputs. After the detailed network results are completed, they will be gradually improved. These strategies help maintain user interest because they reduce the sense of delay.

Results and Discussion

Dataset and Evaluation Metrics

In order to more accurately assess the overall performance and generalization ability of our designed system, we created a detailed high-resolution test set, which includes photos of clothing from the real world and artificially synthesized images. In order to provide a broader basis for evaluating rendering accuracy, reliability, etc., under various conditions, this dataset is designed to include different types of textiles and garment structures.

The digital textile collection includes 715 high-definition multi-view images, featuring cotton, silk, wool, denim, sequined fabrics, and other materials. To increase diversity, each piece of clothing is photographed from different angles under six light sources. These light sources include direct sunlight, a mix of various colors, artificial shadows, etc. Currently, more than 8,000 fully annotated photo data have been obtained, including standardized geometric shapes as well as precise color and reflectance information.

To evaluate the correctness of timing and interaction, we have set up 128 dynamic tests and generate 20 frames of dynamic lighting effects per second. In order to make an accurate comparison, over 300,000 patterns have been created. In addition, these three thousand physical objects are handcrafted according to the design and can be used as references during the testing process. Covering various specific applications of fashion in both the real and virtual worlds.

Evaluation metrics include qualitative and quantitative elements. Using quantitative analysis methods, image quality is assessed through Peak Signal-to-Noise Ratio (PSNR); SSIM is used to measure the overall visual recognizability and spatial correlation of the image; LPIPS is employed as a fine-grained feature similarity metric to identify perceptual detail differences between the reconstructed image and the real image. The compatibility of two RTX4090 high-performance computing devices across multiple generational specifications was also tested. The average angular error of surface normals is used to measure geometric reconstruction and provide a reference standard beyond visual recognizability. The average frame rate of the device platform under normal operating conditions is an indicator of operational efficiency.

Based on the participants' research, 42 users were surveyed about their views on the realism of garment rendering, the preservation of textile details, and the responsiveness of interactions. The evaluation was conducted under different lighting conditions and with different clothing worn. Path tracing images and multi-scale photogrammetry methods provide reliable reference data to validate them. For all the key factors that affect the photorealism of virtual clothing in visualization, there are various evaluation methods that can comprehensively cover them.

Performance Analysis

When compared to mid-range and high-performance systems, this system's functionality and scalability are outstanding. On the Nvidia A100 platform, rendering consistently stays within the 58 FPS range; single-frame latency is approximately 24.3 milliseconds, exceeding 69 seconds under maximum memory usage conditions. In consumer field tests, it demonstrated good stability. It has an average latency of 27 frames per second, an average frame rate of 38.9 milliseconds, and under maximum conditions, it uses over 7.8 GB of memory, while still maintaining good functionality across various device types.

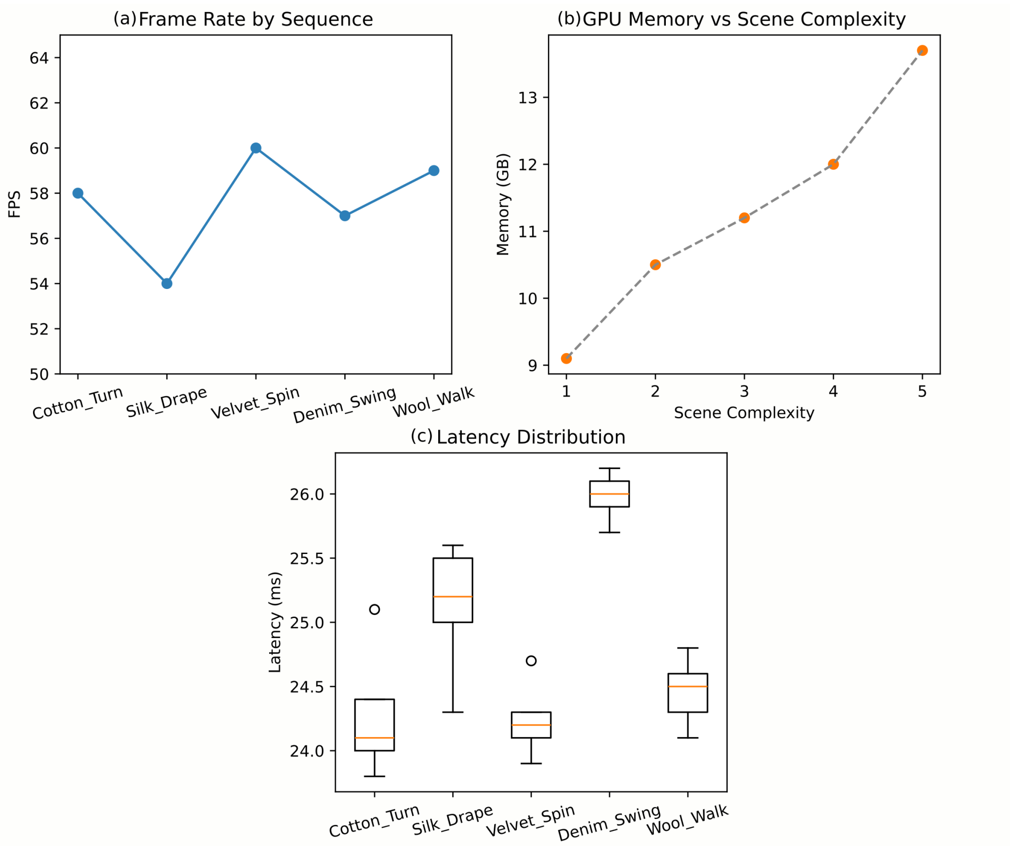

Figure 3. Performance Analysis. (a) Frame Rate Progression on Representative Sequences (b) GPU Memory Usage Relative to Scene Complexity (c) Latency Distribution during Interactive Sessions

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In short, the frame rate (FPS) values exhibit average stability under different types of fabrics, materials, and light sources, with a range deviation of less than four frames. This stability is crucial for the effective and accurate use of interactive functions. The adaptive sampling mechanism can help optimize the allocation of computational resources and reduce redundancy caused by repeated calculations in a visually stable background. In addition, a neural cache has been introduced to ensure stable service for operators and observers, while reducing the impact of rapid camera position changes or unexpected lighting conditions on latency.

Moreover, system reliability is given a high priority, ensuring that the frame drop or loss rate is below 1% in all tests. For applications that require a smooth virtual try-on experience, this limitation is very important. Figure 3 shows a comprehensive evaluation of the system's performance from multiple angles. To demonstrate temporal elasticity and flexibility, Figure 3a shows the frame rate development in several typical garment operation sequences using a line chart. As shown in Figure 3(b), a scatter plot with a regression line can be used to illustrate the relationship between GPU memory consumption, scene complexity, and sequence. Finally, the box plot in Figure 3(c) shows the distribution of rendering latency under interactive use. To illustrate common performance fluctuations and extreme cases, it also shows the distribution of rendering latency.

Therefore, all the above indicators confirm that the aforementioned method not only has high computational efficiency but also can be practically applied under given constraints on hardware resources and user needs.

Comparative Study with Baseline Methods

We compared the performance of this new system with three well-known foundational algorithms that are widely used for high-end garment displays. A mesh renderer based on physical rendering technology, Blender Cycles; a real-time graphics pipeline based on Unreal Engine, showcasing clothing through custom shaders; and a building system based on Neural Radiance Fields (NeRF), specifically tailored for digital clothing. In practical applications, the baseline is established through different combinations of rendering quality, flexibility, and computation.

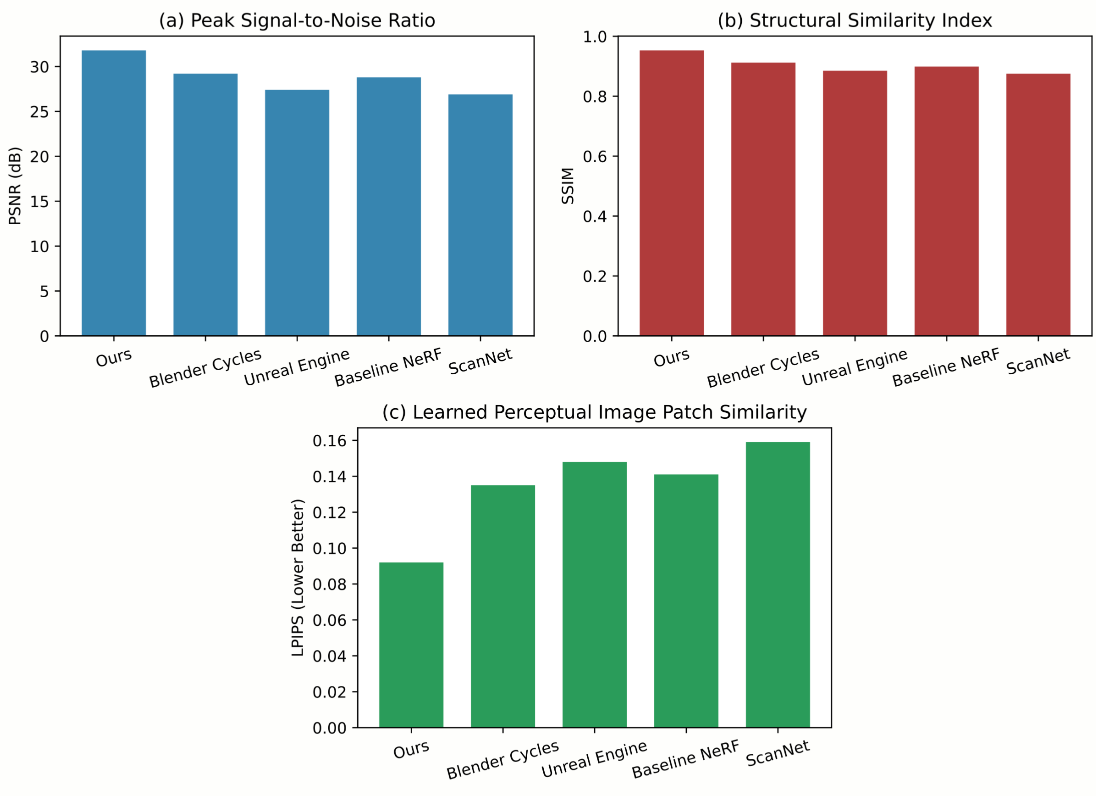

Figure 4. Quantitative Visual Metrics Comparison (a) Peak Signal-to-Noise Ratio (b) Structural Similarity Index (c) Learned Perceptual Image Patch Similarity

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The chart of quantitative data is shown below: Figure 4(a) shows that our method achieves an average peak signal-to-noise ratio of 31.8dB compared to other methods. This indicates that the reconstruction results have higher accuracy and detail under different fabric and lighting conditions. In terms of structural similarity (SSIM) shown in Figure 4b, this also demonstrates that our method maintains structural stability better. Perceptual structure and geometric patterns: Its mean index is 0.953. As shown in Figure 4c, the learned perceptual image patch similarity (LPIPS) indicates that our method is more effective than traditional neural or physics-based methods in preserving the appearance of high-resolution textiles. In addition, it also performs better on textile images with low contrast or complex patterns.

Figure 5 shows a comparison chart under different materials and lighting levels. Figure 5(a) shows the function of time frames, demonstrating how these methods handle lighting changes when objects are moving simultaneously. The box plot depicts the distribution of color retention scores for silk fabric under different color lighting conditions, as shown in Figure (b). This helps determine which method is more resilient to hue changes. The surface texture retention index of velvet materials under low light conditions, as shown in the grouped bar chart in Figure 5(c); it is worth noting that there are significant differences between different renderings.

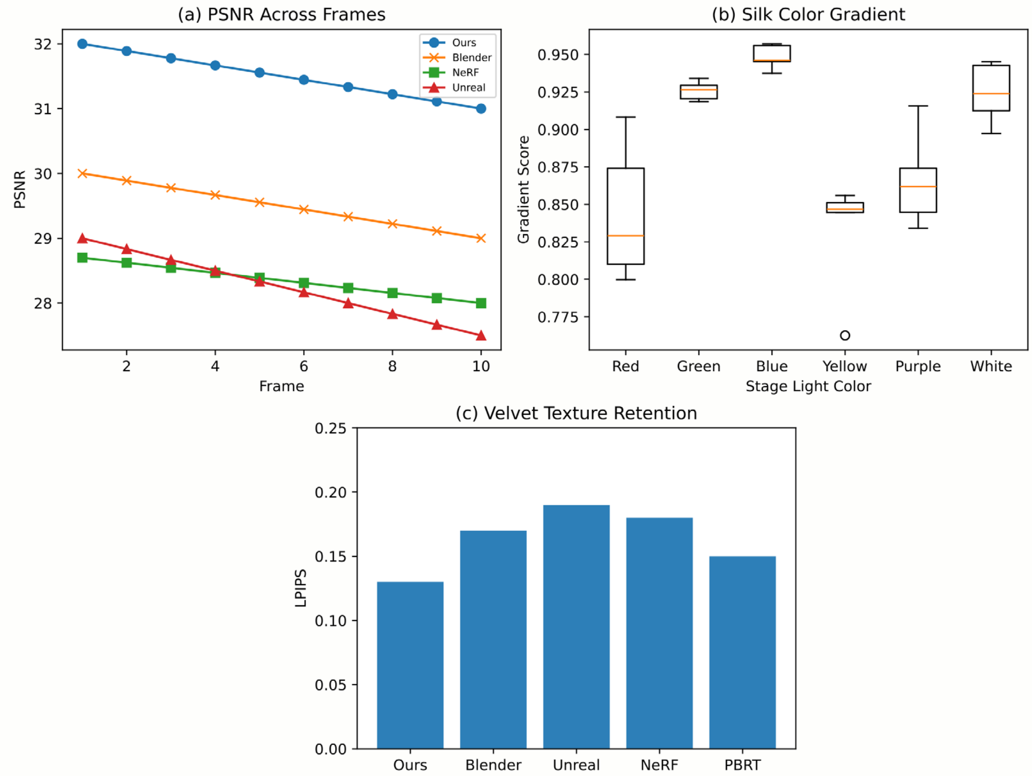

Figure 5. Evaluation under Lighting and Material Variation. (a) PSNR Trends for Brocade Across Dynamic Frames (b) Color Gradient Preservation for Silk Under Multiple Lighting Conditions (c) Surface Texture Retention on Velvet in Low Ambient

In addition, user perception validated the technical data. According to a structured survey of 42 participants, people generally perceive human-made products to be more realistic than artificially made products (Figure 6(a)). According to statistical analysis, any other benchmark is lower than the realism score. The preservation of textile details is shown in Figure 6(b), and our system achieved high scores in both dynamic and static lighting scenarios. Figure 6(c) shows the user experience and system response speed when processing real-time objects. In complex light and shadow scenes, both have significantly improved and maintained a high level of interactivity. In summary, these findings demonstrate the feasibility and acceptance of the proposed interactive digital fashion space approach.

Using the ablation results shown in Figure 7, carefully examine the impact of each architectural component. Figure 7(a) shows the impact of removing the dynamic lighting module on the PSNR values and the highlight recognition error rate per sample time during the testing phase. To provide more information about detail preservation, Figure 7(b) is a scatter plot comparing LPIPS and micro-preservation between model groups with

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and without attention mechanisms. To simultaneously present the comprehensive effects of each ablation variant in our proposed system, Figure 7(c) depicts a combined bar chart.

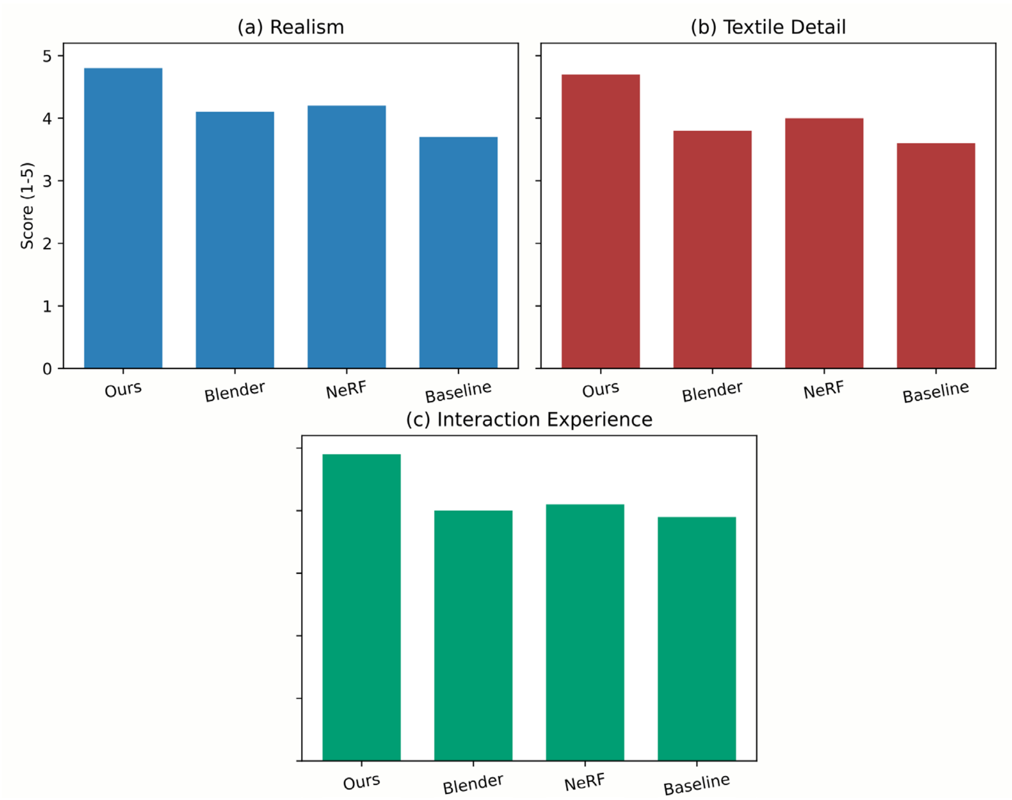

Figure 6. User Perceptual Scores (a) Realism Judgments (b) Textile Detail Ratings (c) Interaction Experience Scores

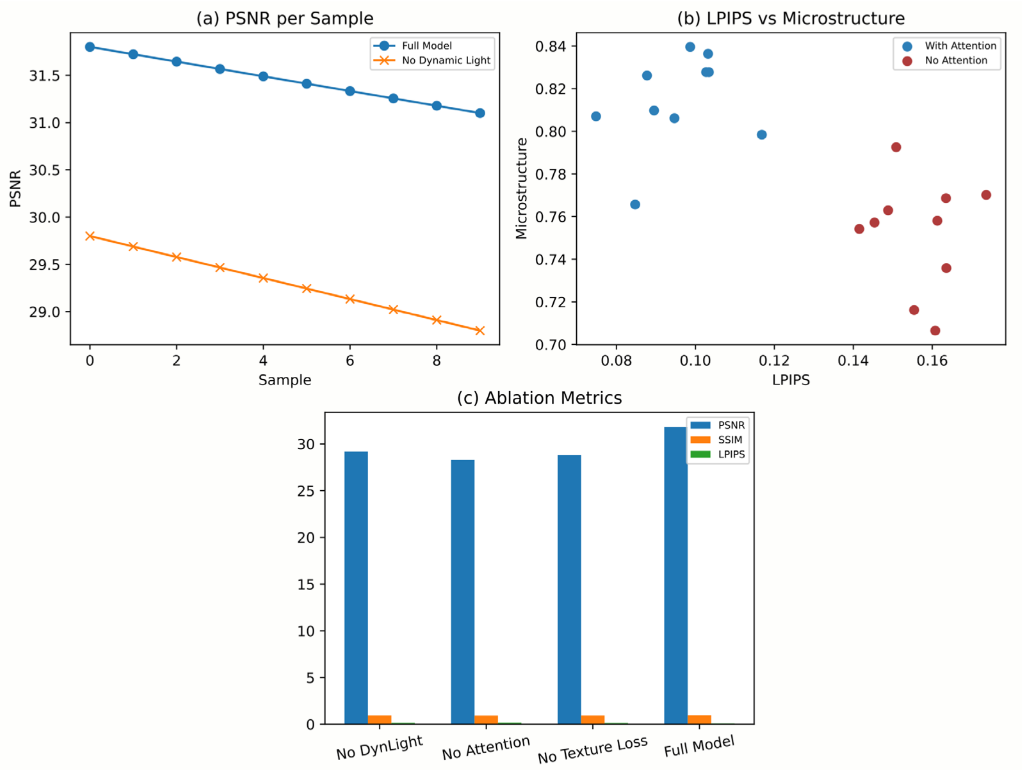

Figure 7. Ablation Study Results. (a) Effect of Dynamic Lighting Removal on PSNR Across Samples (b) LPIPS and Microstructure Retention Scatter Comparison with/without Attention Module (c) Full Model and Ablated Variants Quantitative Comparison

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Combining these comparison-based ablations strictly verifies that the quantitative accuracy, visual details and overall user intuition level of the proposed method for next-generation virtual garment rendering are higher compared with other methods under different test situations.

Conclusion

This paper introduces an advanced data-driven garment representation system aimed at bridging the long-standing gap between computational power and photo-realistic rendering. By integrating calibrated multi-view textile dataset calibration, dynamic light model construction, and the application of material-aware neural attention mechanisms, the proposed work demonstrates comparable or superior image recognition performance compared to current state-of-the-art garment visualization models.

First, the main results of this study are as follows: The complex material behavior dataset collected through high-resolution and multispectral photogrammetry serves as the fundamental reference for garment rendering research. Secondly, this novel network structure achieves high-fidelity textile simulation in various environments through explicit lighting control and learnable fabric-aware feature representation. Third, this system surpasses previous systems by improving GPU inference efficiency to enhance rendering performance and significantly reduce memory usage.

Moreover, experiments have proven this statement. To some extent, by quantitatively evaluating the performance of the system, commonly used quality metrics are compared with traditional physics-based rendering models and newly developed methods such as neural networks. In addition, users have verified that this feature can significantly enhance the perceived realism and interactivity of the user experience under more complex lighting and material conditions. Ablation analysis can easily identify the components that affect the overall system's recognition rate under specific conditions.

In summary, this structure is the best choice for creating high-definition and interactive clothing, as it plays an important role in practical applications such as academic research, virtual fitting, and digital clothing development through immersive interaction. Future research will focus on the model's capabilities in more unusual textiles, non-Lambertian light diffusion scenarios, cross-modal garment transformation methods, and continue to push the limits of physically realistic digital clothing.

Author Contributions

Agnieszka Julia Jankowska contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision. Monika Elżbieta Chmielewska contributes to conceptualization, methodology, software and project administration. All authors have read and agreed with the manuscript before its submission and publication.

Funding

This research received no specific financial support from any funding agency.

Institutional Review Board Statement

Not applicable.

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