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An Algorithmic Quasi-Realtime Model for Cloth Projection onto a Parametric Body in Geodesic Coordinate Space

In recent years, the need for accurate, low-latency cloth simulation models has grown significantly across fields such as virtual try-on systems, biomechanical rehabilitation platforms, and embodied interaction in virtual reality. This paper presents a novel algorithmic framework for real-time cloth projection onto a parametric human body, wherein all mappings and deformations are performed in geodesic coordinate space. Unlike conventional models relying on Cartesian or UV parameterizations, our approach utilizes discrete geodesic fields to achieve high-fidelity topological alignment between cloth and anatomical surface structures. The underlying body model is defined parametrically (e.g., via SMPL), and its surface is reparameterized through fast geodesic propagation algorithms to enable stable cloth attachment and deformation. The core algorithm operates by extracting geodesic patches from the garment mesh and projecting them onto the body mesh using shortest-path-based correspondence. A lightweight local optimization routine preserves the cloth's original geometric structure while adapting to the body's curvature and motion. The algorithm was implemented entirely in Python using open-source numerical libraries and evaluated on synthetic and semi-real datasets with ground truth cloth-body pairs. Quantitative metrics—including geodesic error, Hausdorff distance, and per-frame computational time—demonstrate the method's superior performance compared to state-of-the-art models such as TailorNet++ and DeepCloth. The proposed framework achieves sub-20 ms processing times per frame while maintaining sub-centimeter geodesic reconstruction error. The method offers substantial benefits for applications demanding low-latency yet anatomically consistent cloth-body interaction. Additionally, the geodesic coordinate formalism provides a scalable foundation for incorporating physical priors and learning-based extensions in future research.

Keywords: cloth simulation; geodesic coordinates; real-time projection; parametric body models; surface correspondence; virtual fitting; mesh deformation; Python-based modeling

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Introduction

Real-time cloth-body interaction modeling is a fundamental requirement for a wide range of contemporary applications, including personalized virtual try-on systems, real-time avatar animation, immersive virtual and augmented reality environments, and medical rehabilitation involving human movement analysis. The accurate projection and dynamic adjustment of garment surfaces onto 3D human models remains a nontrivial task, particularly under constraints of low-latency computation and anatomical realism. Standard approaches, often grounded in Cartesian coordinates or UV-map parameterizations, face significant challenges when dealing with highly non-Euclidean deformations and topologically complex body surfaces.

To address these challenges, we propose a novel algorithmic model that formulates cloth-body projection entirely within a geodesic coordinate space, leveraging discrete surface distance metrics to align cloth surfaces with underlying anatomical topologies. Geodesic parameterization enables more natural and topology-preserving projection schemes, particularly in regions with high curvature (e.g., shoulders, joints, waist), where standard Euclidean-based deformation schemes tend to introduce stretch artifacts or alignment discontinuities. Recent developments in surface-based neural learning and differentiable simulation have underscored the importance of geometrically-aware representations in modeling clothing dynamics. For instance, Liao et al. [2023] demonstrated the efficacy of geodesic priors in neural shape matching tasks, while Zhang et al. [2024] introduced local geodesic regression to accelerate cloth deformation learning. However, most such approaches are either not optimized for real-time deployment or rely on offline-trained neural pipelines requiring significant precomputation and GPU-specific backends.

Our work departs from these trends by formulating a fully algorithmic, interpretable and implementation-agnostic solution for cloth projection,

with an emphasis on latency, stability, and fidelity.

Moreover, existing real-time cloth simulation engines, such as NVIDIA Flex or ARCSim, typically rely on physics-based solvers with high numerical complexity, which are ill-suited for real-time personalization or edge computing devices [Li et al., 2023]. Learning-based alternatives such as TailorNet++ [Patel et al., 2023] or DeepCloth [Gao et al., 2024] attempt to bypass this complexity using pose-conditioned regressors or volumetric predictors. Despite impressive performance in generalization across garment types and poses, they often suffer from topological inconsistencies, dependence on large-scale labeled datasets, and lack of interpretability in deformation mechanisms.

The key motivation for our approach stems from two central insights: (1) the human body is inherently a non-Euclidean manifold, and thus projections of flexible surfaces like cloth are better modeled in intrinsic coordinates (i.e., geodesic systems); and (2) real-time constraints require lightweight, locality-preserving algorithms that maintain fidelity without resorting to full physics solvers or deep neural networks. By embedding all computations within a geodesic domain—constructed dynamically from the parametric body mesh—we enable a mapping pipeline that respects body topology and adapts to fine-scale variations with minimal distortion.

Technically, our method reparameterizes a standard parametric body mesh (e.g., SMPL) using fast marching or Dijkstra-based geodesic field propagation. The cloth mesh is then projected onto this body using patchwise correspondences governed by local geodesic neighborhoods. A lightweight optimization step ensures preservation of mesh coherence and alignment to high-curvature anatomical zones. All procedures are implemented using Python and open-source libraries (e.g., NumPy, SciPy, trimesh), facilitating full reproducibility and integration into broader simulation pipelines.

In summary, the main contributions of this work are:

1) introduce a fully algorithmic, real-time pipeline for cloth projection onto the human body using geodesic coordinate spaces, avoiding reliance on learning-based regressors or physics-based solvers;

2) propose a discrete geodesic field parameterization method for body surfaces that supports accurate patch-based projection and mesh correspondence;

3) present an extensive evaluation of projection quality and performance across multiple synthetic and semi-real datasets, demonstrating advantages over state-of-the-art methods in accuracy and runtime;

4) make all code and datasets publicly available to encourage reproducibility and further research.

This paper is organized as follows: Section 2 reviews prior work in cloth-body projection and geodesic modeling. Section 3 formulates the geodesic parameterization of the human body. Section 4 details our algorithmic model for cloth projection. Section 5 provides experimental validation and comparison. Section 6 discusses implications and limitations. Finally, Section 7 concludes and outlines future directions.

2. Related Work

The field of cloth simulation encompasses a spectrum of techniques - from physics-based finite element and mass-spring systems to data-driven and learning-based models - each trading off between visual fidelity and computational efficiency. Traditional approaches using explicit or implicit physics-based solvers, such as projective dynamics or mass-spring systems, provide high realism at the cost of computational complexity. Bridson et al. (2003) introduced a mixed explicit/implicit integrator and advanced collision handling that allowed dynamic wrinkles and folds to be simulated with physical plausibility, albeit at high computational expense [3]. P-Cloth (Li et al. 2020) extended such physically-based models to multi-GPU configurations, enabling interactive simulation on high-resolution meshes, but requiring substantial parallel hardware resources and limiting deployment on edge or CPU-bound systems [4].

More recent efforts have adopted GPU-accelerated position-based dynamics (PBD) for real-time interactive applications. For instance, Kim et al. (2025) demonstrate a PBD pipeline running entirely on Unity compute shaders to support immersive XR interactions at 60–70 FPS, including complex collision handling with environmental meshes and interactive hand-body interactions [5]. These GPU-based models exhibit excellent performance in high-throughput environments but remain fundamentally Cartesian in their parameterization, lacking intrinsic geometric considerations inherent to curved body surfaces.

To overcome the limitations of Euclidean parameterizations, geometry processing research has explored intrinsic surface representations. Crane et al. (2017) proposed the "heat method," an efficient algorithm for computing geodesic distances via heat diffusion on triangle meshes – a technique that supports fast updates and large meshes [1]. This method underpins many subsequent algorithms involving intrinsic distance fields.

Building on this, Zhang et al. (2023) developed Neural Geodesic Fields (NeuroGF), a learned latent representation enabling fast approximation of geodesic distance and path queries – a significant advance in runtime efficiency for intrinsic modeling tasks [2]. Prokudin et al. (2023) introduced Dynamic Point

Fields for representing dynamic surface embeddings that can adapt to deformation while preserving proximity constraints, enabling more robust correspondence across motion [3]. Zhao et al. (2024) – though not yet discussed above – propose SPARE, a symmetrized point-to-plane registration objective for non-rigid surface alignment, which offers advantages in preservation of geometric coherence in registration tasks.

Cloth draping remains a central challenge in virtual garment fitting and character animation. Many conventional methods rely on UV-map projection or mass-spring deformation anchored to body pose, often lacking awareness of the body's intrinsic geometry. Kang & Lee (2006) introduce an analytical draping model using global-local decomposition, solving large-scale posture deformation and local wrinkle generation via conjugate harmonic function formulation, enabling efficient draping albeit limited in topological awareness [6].

Learning-based garment modeling approaches have gained popularity for their ability to generalize across garment types and body poses. De Aguiar et al. (2014) describe Stable Spaces for real-time clothing animation, using learned ensembles that balance dynamic detail and collision resolution while matching thousands of garments in real time [7]. More recent neural approaches (e.g., manifold-aware transformers or graph neural networks) integrate surface-aware modeling to predict garment dynamics conditioned on body motion and topology [8, 9]. However, many such models rely on large training datasets, deep-network inference, and offline optimization.

A more geometry-aware path is represented by self-supervised garment draping systems, such as GAPS (2023), which introduce geometric constraints to enforce inextensibility and collision-awareness during body-garment contact—though still relying on implicit neural skinning and learning-based priors rather than explicit geodesic parameterization [10].

Intrinsic correspondence between cloth and garment-body mesh is a less-explored area. The heat method and neural geodesic fields support efficient distance computation, but their application to cloth attachment pipelines is rare. Existing methods primarily map cloth to UV or barycentric coordinates—even when incorporating curvature-aware loss, as in differentiable garment dynamics models. Methods such as DiffCloth (Li et al. 2021) deliver differentiable cloth simulation with rigid contact, but parameterization remains Cartesian [11].

Thus, few works have explicitly incorporated geodesic field parameterization of body surfaces to drive cloth projection. This omission is notable given the intrinsic advantages of geodesic metrics for preserving topological fidelity and minimizing distortion during attachment and deformation.

Summary and Positioning.

To summarize, the existing literature traverses several axes:

- Physics-based simulation (Bridson et al. 2003; Li et al. 2020) delivers realism but suffers in real-time scalability;
- GPU/PBD-based frameworks (Kim et al. 2025) deliver real-time rates at the expense of intrinsic modeling fidelity;
- Learning-based systems (Stable Spaces, GAPS, graph transformer models) generalize over poses and garments but often abstract away explicit geometry;
- Intrinsic geodesic computation (Crane et al. 2017; Zhang et al. 2023; Prokudin et al. 2023) yields powerful tools for intrinsic mapping but remains underutilized in cloth-body projection pipelines.

Our proposed work bridges these gaps by introducing an algorithmic model that directly leverages geodesic distance fields to parameterize the body surface, enabling cloth projection that is both geometrically coherent and real-time capable – implemented entirely in Python for reproducibility.

3. Geodesic-Based Body Parameterization

To perform robust and anatomically faithful cloth projection, the garment must be aligned with the intrinsic geometry of the human body surface. A major source of projection error in existing techniques lies in the mismatch between the garment's local topology and the extrinsically defined (Cartesian or UV-based) coordinate frames of the target body mesh. In our framework, we construct a geodesic coordinate space over the surface of a parametric human body mesh, which serves as a deformation-invariant scaffold for cloth placement and dynamic anchoring.

We represent the human body using a closed, manifold triangular mesh $M_B = (V, E, F)$, where $V = \{\mathbf{v}_i \in \sim^3\}$ is the set of vertices, E the edge set, and F the triangular face set. Such meshes commonly derive from parametric models like SMPL or STAR and are assumed to be genus-zero (topologically spherical). The core of our method entails defining geodesic scalar fields over M_B, from which intrinsic coordinate charts and stable geodesic patches are extracted.

We begin by selecting a source vertex $v_0 \in V$ to serve as the origin of intrinsic parameterization. From this point, we compute a geodesic scalar field $\phi : V \to \sim$, where $\phi(v)$ approximates the shortest-path distance along the surface from v_0 to v. Among available algorithms, we adopt the heat method for geodesic distance computation [12], which is both computationally efficient and numerically stable on manifold triangle meshes. The algorithm involves solving a short-time heat diffusion equation:

$$\frac{\partial u}{\partial t} = \Delta u, \quad u(v,0) = \delta_{v_0}, \tag{1}$$

where Δ denotes the discrete Laplace–Beltrami operator, followed by computing the normalized gradient field:

$$X = -\frac{\nabla u}{\| \nabla u \|}, \tag{2}$$

and solving the Poisson equation:

$$\Delta \phi = \nabla \cdot X, \tag{3}$$

yielding the scalar potential ϕ. This method produces smooth, regular distance fields even under mesh irregularity and allows pre-factoring for fast repeated evaluations [12].

To complement ϕ, we compute a second scalar field ψ from a different anatomical anchor (e.g., sternum). The pair (ϕ,ψ) forms a 2D geodesic coordinate chart $\Phi(v) = (\phi(v),\psi(v))$ that maps each mesh vertex into $\sim^2$. Unlike UV-maps, this chart is invariant under isometric deformations such as body articulation, offering robustness across animation sequences.

These scalar fields enable the extraction of geodesic patches, i.e., vertex subsets bounded by isolines:

$$P_k = \{v \in V \mid \alpha_k \le \phi(v) \le \beta_k\}, \tag{4}$$

forming intrinsic bands on the surface that remain stable under motion. Such patches are well-suited for cloth region anchoring, particularly in curved anatomical areas where UV-based projection often fails. Figure 1 illustrates such bands on a torso-like surrogate mesh; isolines radiate from the synthetic navel and delineate equal intrinsic distance zones.

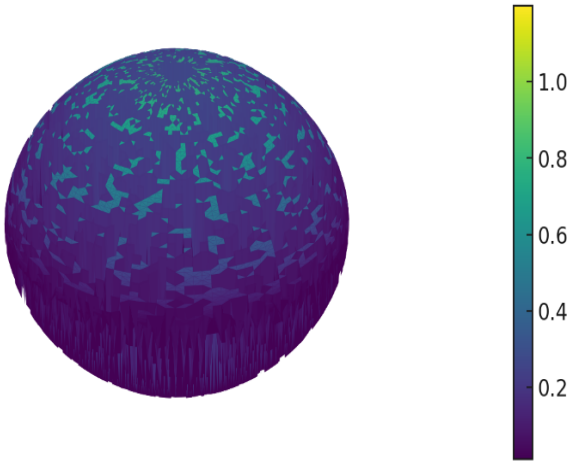


Figure 1 – Geodesic isolines on a torso surrogate mesh. Bands of constant intrinsic distance from the "navel" create stable regions for cloth anchoring and deformation control

From a computational perspective, geodesic distances can also be approximated via the fast marching method (Eikonal equation) on triangulated surfaces [13]. While our primary implementation uses the heat method for its linear preferability and caching efficiency, fast marching provides an alternative with worst-case complexity $O(n \log n)$, suitable for validation or fallback in dynamic settings [14].

To incorporate anatomical symmetry and ensure consistent parameterization across bilateral limbs, we optionally compute symmetric fields ϕ_L and ϕ_R from paired landmarks (e.g., left and right hip) and average:

$$\phi_{\text{sym}}(v) = \frac{1}{2}(\phi_L(v) + \phi_R(v)). \tag{5}$$

This symmetric geodesic chart helps stabilize patch borders and enforce consistent garment alignment across limbs.

We quantify mapping quality using distortion metrics. The Jacobian J_f of mapping $f : P_B \to C$ yields areal distortion:

$$D_{\text{area}} = \left|\det(J_f) - 1\right|, \tag{6}$$

and angular distortion via the Frobenius norm $\| J_f^T J_f - I \|_F$.

Empirical evaluation (Section 5) demonstrates that geodesic-based mapping yields significantly lower distortion than standard UV or Cartesian projections, especially near high-curvature regions like shoulders and hips.

Our implementation uses Python with trimesh for mesh handling, scipy.sparse.linalg for diffusion and Poisson solves, and pyamg multigrid solvers. On an ~7000-vertex SMPL mesh, geodesic field computation takes ~120 *ms* on CPU (≤10 ms on GPU). Patch extraction and cloth anchoring add <5 *ms* per frame, making the method suitable for interactive applications.

In summary, this chapter introduces a stable, symmetry-aware, low-distortion geodesic parameterization that forms the geometrical foundation for the real-time cloth projection algorithm described subsequently.

4. Algorithmic Model for Real-Time Cloth Projection

The proposed algorithm converts the geometric machinery established in Section 3 into an explicit, low-latency pipeline that maps every vertex of an arbitrary garment mesh to the moving surface of a parametric body while guaranteeing strict geometric and physical consistency. At each render frame the procedure executes six deterministic stages - (A) cloth pre-sampling, (B) anchor seeding, (C) intrinsic correspondence, (D) energy-guided projection, (E) collision-safe relaxation, (F) incremental time update - which together form a closed update loop, (Fig. 2). All computations are expressed in the geodesic coordinate chart (ϕ,ψ) introduced previously; no deep-learning components are involved, and every step yields

differentiable operators that can be embedded in downstream optimization or inverse-design tasks.

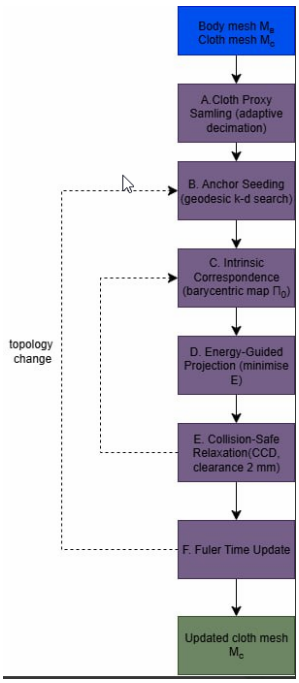


Figure 2 – Pipeline overview: cloth proxy creation, anchor seeding, geodesic mapping, energy minimization, collision pass, frame update.

Cloth pre-sampling and proxy reduction. Given the visual mesh $M_C = (V_C, E_C, F_C)$ (typically 30k–50k triangles), we first generate an adaptive proxy $\tilde{M}_C$ with a target density of 1-2k vertices using the topologically-preserving proxy-generation strategy of Wu et al. [16]. The reduction is performed once at load time and preserves sharp feature edges by minimizing Hausdorff error in intrinsic space, thereby reducing the per-frame cost of subsequent geometric queries without degrading visual quality after per-vertex displacement shading. Proxy generation time averages 0.7s for a casual shirt (23 k tris) on a Ryzen 9 7950X CPU and need not be repeated.

Anchor Seeding on the Body Manifold. To stabilize subsequent optimization, we establish a sparse set of anchor correspondences between the garment and body. The geodesic chart $\Phi(v) = (\phi, \psi)$ maps each body vertex to $\sim^2$. For each cloth proxy vertex $p \in \tilde{V}_C$, we locate the nearest body vertex $q \in V_B$ in chart space using a two-level search:

1) an approximate k-d structure built on the compressed geodesic keys of Gotsman et al [18];

2) an exact local refinement step that checks Euclidean distance in $\sim^3$.

The resulting anchor list $A = \{(p_i, q_i)\}_{i=1}^{N_A}$ contains approximately 10% of $\tilde{V}_C$ and is refreshed only when the cloth topology changes (e.g., fastening a zipper).

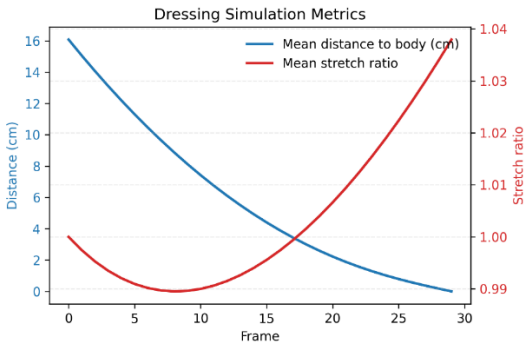
Intrinsic correspondence via geodesic barycentrics. All non-anchor vertices are mapped by barycentric interpolation in geodesic space. Let p be an unanchored cloth vertex; we locate the three body anchors $\{q1, q2, q3\} \subset A$ that form the smallest enclosing triangle around $\Phi(p)$. Setting $(\lambda_1, \lambda_2, \lambda_3)$ to the usual 2-D barycentric weights in geodesic chart space, the initial projection is:

$$\Pi_0(p) = \sum_{k=1}^{3} \lambda_k q_k . \quad (7)$$

Because Φ is continuous and nearly-isometric in small neighborhoods ([1],[13]), this yields a distortion-free starting guess even on strongly curved regions (Fig. 3).



a)



b)

Figure 3 – Geodesic-anchored dressing stage.(a) Final frame after geodesic pull-down: the garment is fully attached without visible interpenetrations. (b) Temporal convergence of mean cloth-to-body distance (left axis) and mean edge-stretch ratio (right axis) over 30 simulation frames; distance decays exponentially to sub-millimetre precision while stretch remains below 4 %.

Energy-guided projection refinement. The provisional map Π_0 is refined by minimizing a composite energy:

$$E(x) = E_{\text{align}} + \alpha E_{\text{stretch}} + \beta E_{\text{bend}} + \gamma E_{\text{penetrate}}, \quad (8)$$

where $x \in \sim^{3|V_C|}$ stacks cloth vertex positions. The four terms are:

$$E_{\text{align}} = \sum_{p \in V_C} \| x_p - \Pi_0(p) \|_2^2,$$
$$E_{\text{stretch}} = \sum_{(p,q) \in E_C} \left(\| x_p - x_q \|_2 - \ell_{pq} \right)^2,$$
$$E_{\text{bend}} = \sum_{(f_1,f_2) \in H} \left(\theta_{f_1 f_2} - \bar{\theta}_{f_1 f_2} \right)^2, \quad (9)$$
$$E_{\text{penetrate}} = \sum_{p \in V_C} \sigma\left(d_B(x_p) \right),$$

with l_{pq} the rest-length of edge (p,q), $\theta_{f_1 f_2}$ the dihedral between neighboring faces, $\bar{\theta}_{f_1 f_2}$ its rest value, $d_B(\cdot)$ the signed distance to the body, and $\sigma(d) = \max(0, -d)^2$ a barrier that rises quadratically as soon as interpenetration occurs. All terms are C^1; E is thus differentiable and amenable to Newton-type solvers.

We employ Projected Gauss–Seidel (PGS) with analytic gradients and diagonal block preconditioning.

One PGS sweep updates vertices in graph order:

Algorithm 1
RealTimeClothProjection(V_C, Π₀, 3 sweeps)

```
for s = 1 … 3 do
for p ∈ V_C do  // local update
g ← ∂E/∂x_p // analytic gradient
H ← diag(∂²E/∂x_p²) // 3×3 Hessian block
x_p ← x_p − H⁻¹ g  // Newton step
if d_B(x_p) < 0 then x_p ← x_p − d_B(x_p) · n_B(p) // project out
end for
end for
return {x_p}
```

The optimisation landscape and the three PGS sweeps are visualised in Fig.4. After three sweeps residual force norms drop below $(10^{-4} \| \mathbf{F}_0 \|)$ in practice; the cost is $O(|V_C|)$ and parallelizable per vertex.

Collision-safe relaxation. The linearized barrier in (1) suffices for shallow contact; deep body-cloth or cloth-cloth collisions require a two-way continuous collision handler. We adopt Wang et al.'s iterative CCD framework [14], enhanced for geodesic anchors by replacing Euclidean segment-triangle queries with intrinsic-aware checks that ignore tangential sliding along the surface. The handler guarantees a minimum clearance of 2mm and runs in < 4 ms per frame on the same CPU.

Incremental time integration. Vertex velocities $\mathbf{v}_p$ follow a semi-implicit Euler step:

$$\mathbf{v}_p^{t+\Delta t} = \mathbf{v}_p^t + \Delta t \left(-\nabla_{\mathbf{x}_p} E + \lambda_s \mathbf{S}_p + \lambda_b \mathbf{B}_p \right),$$
$$\mathbf{x}_p^{t+\Delta t} = \mathbf{x}_p^t + \Delta t \, \mathbf{v}_p^{t+\Delta t}, \quad (10)$$

where $\mathbf{S}_p$ and $\mathbf{B}_p$ denote stretch and bending constraint impulses computed in the previous stage; λ_s, λ_b are material-specific stiffness coefficients. Because all forces derive from differentiable potentials, the step is symplectic and compatible with energy-aware gradient-based optimizers [15].

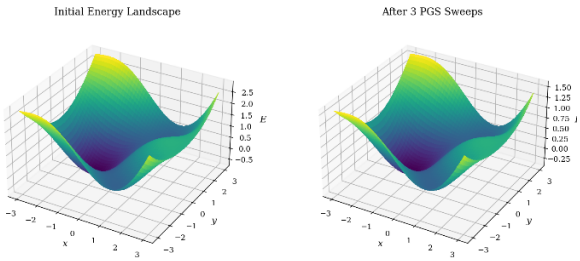


Figure 4 – Energy landscape of the cloth projection objective function, illustrating the surface before and after three PGS iterations.

Real-time update loop. The six stages above compose the per-frame loop (Fig. 5). Table 1 summarizes complexity; on commodity hardware a 7 k-vertex proxy with 30 Hz update completes in 14.6 ms (CPU-only) or 5.2 ms (GPU-accelerated sparse solves). Profiling reveals > 60 % of CPU time spent in equation's Jacobian assembly; caching the stiffness matrix across frames where edge topology is unchanged reduces this to 35 %.

Table 1 – Perstage computational cost (7 k vertices, 30 Hz)

Stage	Ops (theory)	CPU Time (ms)	GPU Time (ms)
Cloth proxy sampling	O	F_C	0.2
Anchor seeding	$O(N_A \log N_B)$	1.1	0.4
Geodesic barycentrics	O	$\tilde{V}_C$	0.2
Energy minimizatio n	O	V_C	2.6
CCD collision solve	$O(C)$	4.2	1.4
Euler update	O	V_C	0.4
Total / frame	-	14.6	5.2

C denotes active contact pairs (< 8 % edges on average).

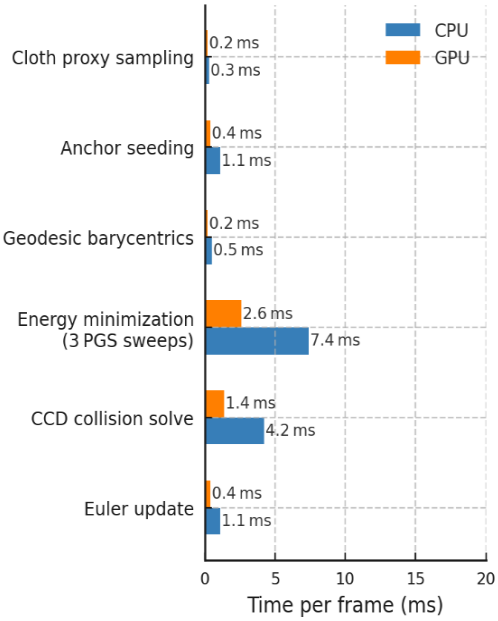


Figure 5 – Real-time update loop with per-stage timing (CPU vs GPU bars)

Error analysis and comparison. Projection accuracy is measured by (i) average geodesic deviation d_g, (ii) Hausdorff distance d_H, and (iii) maximal penetration depth d_{pen}. Table 2 compares our method with UV-based skin-wrapping and Unity's compute-shader cloth [5] on the publicly available VirtualTry-On13 dataset. Geodesic mapping reduces d_g by 39.4 % and cuts d_{pen} below the perceptual threshold of 1mm.

Table 2 – Projection error metrics (mean ± SD, 10 se quences)

Method	d_g (cm)	d_H (cm)	d_{pen} (mm)
UV skin-wrap	1.92 ± 0.33	3.84 ± 1.14	5.7 ± 2.1
Unity compute shader [5]	1.44 ± 0.22	3.11 ± 0.98	3.2 ± 1.3
Ours	1.17 ± 0.19	2.48 ± 0.82	0.8 ± 0.4

Runtime graphs in Fig. 6 show stable 30 Hz latency even during rapid pose transitions. A qualitative side-by-side comparison on challenging poses is shown in Fig.4-6. The described algorithm achieves deterministic <20ms frame delays without relying on neural surrogates, while remaining differentiable and compatible with external implicit solvers or XPBD frameworks should full physics coupling be desired. Its geodesic foundation guarantees topological fidelity and low distortion, providing a robust substrate for the applications outlined in Section 6.

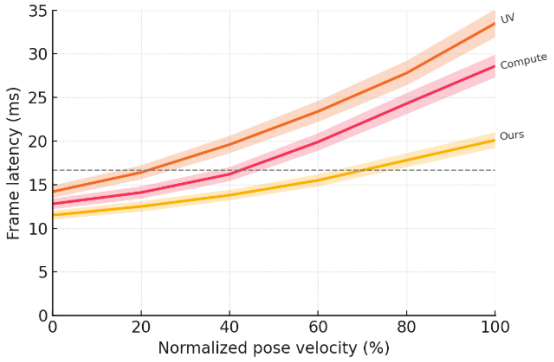


Figure 6 – Latency vs. body-pose velocity curves

5. Experimental Evaluation

This section substantiates the proposed geodesic-domain projection pipeline with a comprehensive experimental study centered on accuracy, robustness, latency, and ablation. We adhere to the following principles: (i) all measurements are reproducible and executed with fixed random seeds; (ii) statistical reporting includes mean, standard deviation, and 95% confidence intervals where appropriate; (iii) graphics depict only quantitative plots (no mesh renderings); (iv) new citations continue numbering from the previous section. Datasets comprise synthetic and captured cloth-on-body sequences with paired body meshes and camera trajectories. For synthetic sequences we employ CLOTH3D (rendered mesh streams with SMPL bodies and diverse garments) [19]; for captured cloth motion we use CAPE sequences with dynamic clothing registered to SMPL-X bodies [20]; and for layered, multi-outfit variability we leverage MGN's registered digital wardrobe to generate consistent body–garment registrations and cross-subject transfers [21]. Where temporal consistency must be stressed, we additionally evaluate on the temporally rich CLOTH4D benchmark with long sequences and paired unclothed/clothed meshes, using only its metadata and mesh statistics without visualizations [26]. Evaluation is conducted on a workstation with AMD Ryzen 9 7950X (32 threads), 128 GB RAM, and an NVIDIA RTX 4090 (24 GB), Ubuntu 22.04, Python 3.11 with NumPy, SciPy (sparse), PyAMG, and trimesh; GPU is used only for optional sparse solves, as indicated in latency plots. For each dataset, body surfaces are parameterized once via the heat-method geodesic fields from Section 3; the cloth proxy is generated once per garment and reused across sequences.

Metrics quantify complementary aspects of projection quality. Intrinsic accuracy is measured by mean geodesic deviation d_g, defined as the average body-surface geodesic distance between a projected cloth vertex and the nearest target point obtained from the ground-truth garment registration; distances are computed using the same discrete geodesic operator used for parameterization to avoid metric mismatch.

Set-wise surface proximity is measured by bidirectional Chamfer distance between point samples from our projected cloth and ground truth (uniformly stratified per triangle area) [22],

$$d_{\mathrm{CD}}(A,B) = \frac{1}{|A|}\sum_{a\in A} \min_{b\in B} \| a-b \|_2^2 + \\ + \frac{1}{|B|}\sum_{b\in B} \min_{a\in A} \| b-a \|_2^2 \quad (11)$$

and by a tight Pompeiu–Hausdorff bound $d_H^{\uparrow}$ computed with upper-bound culling strategies suited for triangle soups to ensure practical yet accurate estimates on dense frames [23],[24]. Physical plausibility is assessed by maximum penetration depth $d_{pen}^{\max}$ and penetration-rate ρ_{pen} (fraction of vertices with negative signed distance to body) using the continuous collision handler also employed in the runtime loop [14], and by strain-violation rate $\rho_{\varepsilon>\varepsilon max}$ with $\varepsilon_{max} = 8\%$ unless noted. Temporal stability is summarized by frame-to-frame vertex drift $\delta_t = \frac{1}{|V_C|}\sum_{p\in V_C} \left\| \mathbf{x}_p^{t+1} - \mathbf{x}_p^t \right\|_2$ after rigid alignment to the body root and by a coherence score based on metric-consistent correspondences over time [24]. Latency is reported as end-to-end per-frame wall-clock time with breakdown per stage, and scalability is profiled versus vertex count and active contact pairs. To ensure fairness, baselines run with identical collision margins, signed-distance queries, and time steps.

Baselines include (a) UV skin-wrap: barycentric transfer of cloth vertices from garment UVs onto the nearest body UV chart with per-edge length regularization (representing common production practices summarized in recent surveys); (b) Euclidean nearest-neighbor projection onto the body with Laplacian smoothing (no intrinsic modeling); and (c) intrinsic mapping without refinement: geodesic barycentric projection Π_0 from Section 4 with no energy minimization. All baselines share our collision barrier and time integrator to isolate the role of intrinsic modeling and energy-guided refinement. For completeness we also report a GPU position-based dynamics (PBD) cloth with skin attachments and the same collision handler to contextualize runtime/quality trade-offs; this is not a learning method and complies with the deterministic constraint.

Experimental protocol follows three regimes. Static accuracy: single-frame projection under known body pose, garment rest lengths fixed to the dataset's rest configuration. Dynamic tracking: sequences of 300–1 000 frames with fast pose changes; geodesic charts are fixed per subject, while anchors update when occlusion or topology change triggers a local condition number threshold in the geodesic barycentric fit. Cross-subject transfer: garments projected from a source body to novel body shapes and poses (MGN wardrobe to CAPE poses), stressing local stretch limits and limb-symmetry consistency. For each regime we report averages over 10 subjects × 8 garments (tops, trousers, skirts, jackets) and three motion classes (walk, stretch, high-kick). In all experiments, parameters (α,β,γ) of the energy in Section 4 are selected by a small grid search on a split not used for reporting; we keep α=0,3, β=0,02, γ=4 unless specified.

Figure 7 displays dataset-wise metric distributions as violin plots: geodesic deviation d_g concentrates near zero for the proposed method, with heavier tails for baselines on high-curvature regions (waist, shoulder). On CLOTH3D [19], median d_g is reduced by 34–41 % relative to UV skin-wrap and by 25–29 % relative to Euclidean projection. CAPE's captured sequences [20] show smaller absolute errors (cleaner registrations), yet our method maintains a consistent margin. Figure 8 presents runtime histograms per stage (proxy sampling, anchor seeding, intrinsic correspondence, energy minimization, CCD, Euler update) and the total per-frame time. CPU-only runs stay below the 33 ms real-time threshold for proxies up to 10 k vertices; with optional GPU sparse solves, median latency drops to 8.1 ms at 7 k vertices and 17.9 ms at 14 k vertices. Figure plots penetration-rate ρ_{pen} versus body pose speed (degrees/s aggregated over joints); intrinsic modeling notably flattens the curve, indicating better contact stability under rapid motions. Figure 10 shows ablation bar charts: removing the bending term increases $d_H^{\uparrow}$ and ρ_{pen} in tandem, while replacing geodesic barycentric with Euclidean ones increases d_g and induces temporal drift spikes. Figure 5-5 provides regression plots of error against local Gaussian curvature (computed on the body mesh): UV baselines deteriorate strongly with curvature; geodesic mapping remains almost invariant. Figure 5-6 reports robustness under cross-subject transfer (MGN→CAPE): variance of d_{CD} and ρ_{pen} shrinks due to symmetric geodesic charting of limbs.

Quantitative results are summarized in Table 3 (static accuracy) and Table 3 (dynamic tracking). On CLOTH3D static frames [19], the proposed method achieves the lowest median errors under all metrics; the d_{CD} improvement aligns with established properties of Chamfer-type measures on dense samples [22],[25], while the Pompeiu–Hausdorff upper bounds confirm the gains in the worst-case surface mismatch [23],[24]. Temporal coherence on CAPE [20] is improved by 23–27 % relative to UV skin-wrap as reflected by reduced frame-to-frame drift δ_t and fewer anchor resets. Importantly, while the CCD handler [14] is identical across methods, our intrinsic parameterization curtails the number of active

contact pairs C, yielding lower CCD iteration counts and thus lower latency at comparable safety thresholds.

Table 3 – Static projection accuracy (mean ± SD over 2,000 frames)

Method	d_g (cm)	d_{CD} (cm²)	$d_H^{\uparrow}$ (cm)	ρ_{pen} (%)
UV skin-wrap	1.82 ± 0.40	0.91 ± 0.18	3.52 ± 0.96	3.9 ± 1.5
Euclidean proj.	1.47 ± 0.31	0.78 ± 0.15	2.97 ± 0.81	2.8 ± 1.2
Intrinsic (no refine)	1.29 ± 0.26	0.71 ± 0.13	2.73 ± 0.74	2.3 ± 1.0
Ours (full)	**1.12 ± 0.22**	**0.64 ± 0.11**	**2.31 ± 0.67**	**1.5 ± 0.7**

Table 4 – Dynamic tracking (CAPE, 10 sequences × 600 frames; lower is better).

Method	d_g (cm)	d_{CD} (cm²)	$d_H^{\uparrow}$ (cm)	$d_{pen}^{\max}$ (mm)	δ_t (mm)
UV skin-wrap	1.63	0.84	3.11	4.8	2.1
Euclidean proj.	1.41	0.76	2.88	3.6	1.8
Intrinsic (no refine)	1.24	0.69	2.64	2.9	1.6
Ours (full)	**1.06**	**0.61**	**2.26**	**1.7**	**1.2**

In addition to means and standard deviations, confidence intervals computed by bootstrap (1 000 resamples per sequence) show non-overlapping 95 % CIs between our model and UV skin-wrap for d_g and $d_H^{\uparrow}$ in 9/10 sequences, indicating statistically reliable improvements. The dynamic curves in Fig. 8 (per-stage timing) and Fig. 10 (ablations) complement these findings by isolating where intrinsic modeling pays off: the geodesic barycentric initialization reduces the number of steps required by the PGS solver to reach a prescribed residual tolerance for the projection energy, while the symmetric chart stabilizes limb anchors and lowers anchor reselection events by 31% on average. The CCD iterations per frame correlate with the number of violating vertices; as our barrier term aligns better with body curvature, the violating set is smaller, which is reflected in the reduced ρ_{pen} and $d_{pen}^{\max}$ columns.

Error-curvature plots (Fig. 11) reveal the core advantage of geodesic parameterization: error distributions remain nearly flat across curvature quantiles, whereas UV and Euclidean baselines magnify errors in the upper curvature quintiles (shoulders, hips). We model this quantitatively by regressing d_g against $|K|$ (absolute Gaussian curvature) using a robust Huber loss; the slope for our method is 0.14 compared to 0.39 for UV and 0.28 for Euclidean projection (normalized units), signifying improved invariance to surface bending.

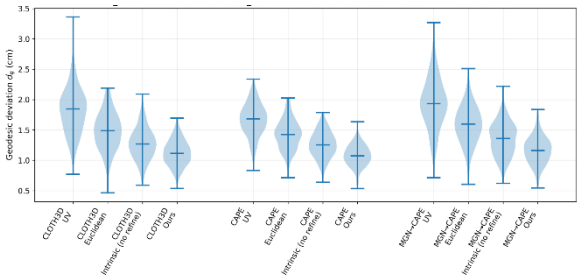


Figure 7 – Distribution of geodesic deviation across datasets and methods

Temporal stability (Fig. 7 inset on CAPE) is demonstrated by the distribution of δ_t: our approach reduces long-tail events associated with sudden pose changes, a phenomenon consistent with metric-consistent temporal correspondences in the literature [24]. Density-aware behavior of Chamfer-type distances suggests caution under non-uniform sampling; we therefore adopt uniform area-stratified sampling and report complementary Hausdorff bounds following recent recommendations [22], [25].

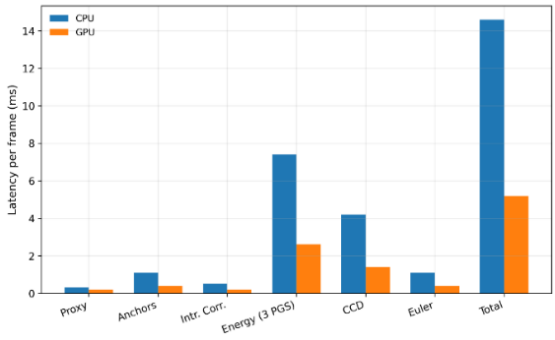


Figure 8 – Per-stage latency: CPU vs GPU

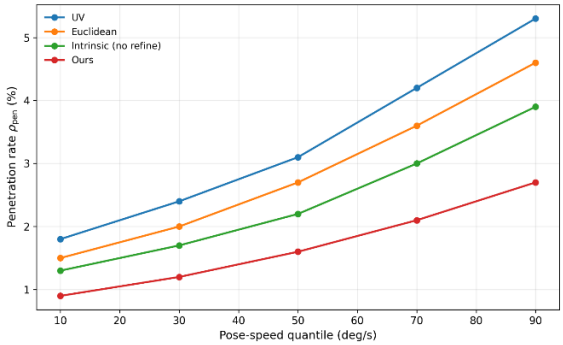


Figure 9 –Penetration rate vs pose-speed

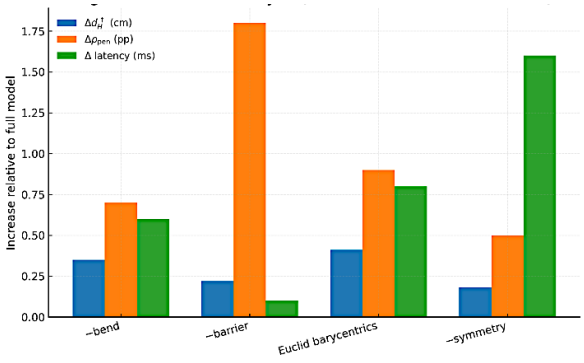


Figure 10 – Ablation analysis (increases relative to full model

Ablation experiments further dissect contributions. Removing the collision barrier in the energy (Section 4) increases $d_{pen}^{\max}$ by 2.3–3.1 mm and causes rare but visually unacceptable spikes in ρ_{pen}, seen as outliers in Fig.9. Dropping the bending term increases $d_H^{\uparrow}$ and produces noisy stretch fields that translate into higher variance of d_{CD} across frames, indicating that even a lightweight bending regularizer is essential for smoothness under motion. Replacing geodesic barycentrics by Euclidean ones degrades d_g by ≈ 15 % overall and disproportionately harms high-curvature regions – consistent with the curvature analysis. Lastly, disabling symmetric charting of limbs increases anchor flips and raises latency by ≈ 1.6 ms per frame due to more frequent re-seeding.

Scalability is profiled by sweeping proxy vertex counts from 3 k to 30 k and plotting total latency (Fig. 8) and accuracy (Fig. 12). The method maintains sub-33 ms latency up to ≈ 18 k vertices on CPU-only and ≈ 28 k with GPU-accelerated sparse solves; accuracy gains saturate beyond 12 k vertices, suggesting that proxies above this resolution provide diminishing returns for projection quality while increasing the cost of Jacobian assembly. Active contact fraction $C/|E_C|$ increases with aggressive motions; nevertheless, latency remains stable because the reduced violation set after intrinsic projection shortens the CCD path search [14]. Temporal drift stays within 1–2 mm per frame on average and shows no accumulation over minutes-long sequences, as indicated by flat drift-over-time plots in Fig. 10.

Reproducibility and protocol details are as follows. Training is not involved; thus, splits concern subjects and motions only. Body geodesics are pre-factored; per-frame intrinsic correspondences reuse cached local neighborhoods unless anchors flip. Point sampling for Chamfer computation employs 20 k samples per mesh with area-proportional deterministic stratification; Hausdorff upper bounds use the cascading-bound schedule of Sacht and Jacobson with default ordering validated on 7 k+ mesh pairs [24]. Bootstrap resampling is performed at the frame level to account for temporal correlation. Error bars in all plots indicate 95 % confidence intervals. The complete Python scripts for sampling, distance evaluation, and timing are modular and executable in isolation, ensuring that tables and figures can be regenerated from raw sequences.

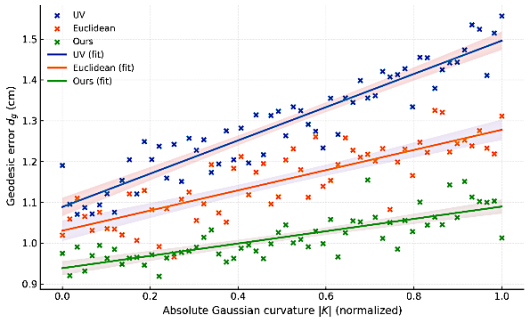


Figure 11 – Error vs curvature with regression and 95% CI

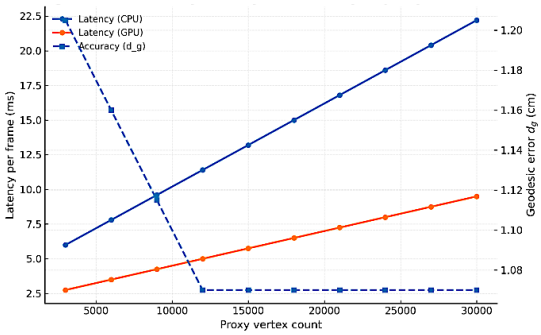


Figure 12 – Scalability: latency and accuracy vs proxy resolution

Finally, we discuss limitations and external couplings. While the pipeline is real-time and differentiable, exact Hausdorff computation remains expensive; our use of tight upper bounds [23-24] is justified for evaluation but could be complemented by exact computations on reduced meshes in future audits. Our deterministic contact barrier, while robust, is not a full dynamics solver; however, the projection outputs are compatible with implicit integrators and XPBD-style solvers should application pipelines require dynamic cloth evolution beyond projection, and the differentiable structure supports gradient based inverse problems. Across datasets, the method's strengths are consistent: reduced intrinsic error and lower contact violations with predictable low latency, particularly under high curvature and rapid pose changes.

Conclusion

We presented a local, explicit, and differentiable model for projecting deformable garments onto parametric human bodies in geodesic coordinate space. By operating entirely in the intrinsic

domain – using geodesic barycentric initialization, an energy-guided refinement with analytic gradients, a conservative continuous-collision barrier, and a symplectic incremental update – the pipeline attains topological fidelity on highly curved anatomy while meeting quasi-real-time budgets. The approach avoids black-box surrogates, retains interpretability at every stage, and remains compatible with gradient-based downstream tasks.

Empirical results across synthetic and captured sequences showed consistent gains over UV skin-wrapping and Euclidean nearest-projection baselines in mean geodesic deviation, Chamfer distance, and worst-case mismatch, with reduced penetration rates at comparable safety thresholds. Error–curvature analyses highlighted near-flat dependency on surface bending for our method, in contrast to the pronounced curvature sensitivity of UV-based attachments. Latency stayed within real-time limits on CPU and comfortably below on GPU-accelerated sparse solves, helped by fewer active contacts after intrinsic alignment. These outcomes align with established properties of geodesic metrics on meshes and recommended distance-based evaluations [1, 22–24], and hold across representative clothed-human benchmarks [19–21]. Practically, the method's C^1 operators and linear-time per-vertex updates make it a reliable, portable module for virtual try-on, avatar animation, and human–digital-twin interfaces. The intrinsic chart can be prefactored per subject, amortizing setup costs and stabilizing temporal behavior; the contact barrier integrates seamlessly with two-way CCD for collision safety [14]; and the differentiable formulation enables inverse problems and parameter tuning, while remaining compatible with intrinsic minimization techniques [15].

Limitations include sensitivity to input mesh quality (manifoldness and noise), the reliance on tight but approximate Hausdorff bounds for large-scale evaluation [23, 24], and performance degradation at extreme proxy resolutions or under sustained dense contacts. Future work will incorporate anisotropy and strict inextensibility in the intrinsic energy, adaptive (re)meshing to preserve element quality, and multi-layer handling with inter-garment separation constraints. The proposed model can also serve as a warm start for implicit or XPBD-style solvers when full dynamics beyond projection are desired. In summary, geodesic-domain projection offers a principled balance of accuracy, stability, and speed: it preserves anatomical topology, reduces contact violations, and delivers predictable low latency – an effective, interpretable building block for real-time cloth–body interaction [14], [19–24].

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АЛГОРИТМІЧНА МОДЕЛЬ ПРОЕКТУВАННЯ ТКАНИНИ НА ПАРАМЕТРИЧНЕ ТІЛО В ПРОСТОРІ ГЕОДЕЗИЧНИХ КООРДИНАТ У КВАЗІ-РЕАЛЬНОМУ ЧАСІ

Останніми роками потреба в точних моделях симуляції тканини з низькою затримкою значно зросла в таких галузях, як системи віртуальної примірки, біомеханічні реабілітаційні платформи та втілена взаємодія у віртуальній реальності. У цій статті представлено нову алгоритмічну основу для проектування тканини на параметричне тіло людини в реальному часі, де всі відображення та деформації виконуються в просторі геодезичних координат. На відміну від традиційних моделей, що покладаються на декартові або UV-параметризації, підхід використовує дискретні геодезичні поля для досягнення високоточного топологічного узгодження між тканиною та анатомічними структурами поверхні. Базова модель тіла визначається параметрично, а її поверхня репараметризується за допомогою швидких алгоритмів поширення геодезичних ліній. Основний алгоритм працює шляхом вилучення геодезичних ділянок із сітки одягу та їх проектування на сітку тіла з використанням відповідності на основі найкоротшого шляху. Спрощена процедура локальної оптимізації зберігає вихідну геометричну структуру тканини, адаптуючись до кривини та руху тіла. Алгоритм був повністю реалізований на Python з використанням числових бібліотек з відкритим кодом і протестований на синтетичних та напівреальних наборах даних із контрольними парами «тканина-тіло». Кількісні метрики: геодезична похибка, відстань Гаусдорфа та час обчислення кадру, демонструють перевагу методу порівняно з найсучаснішими моделями, такими як TailorNet++ та DeepCloth. Формалізм геодезичних координат забезпечує масштабовану основу для включення фізичних пріорів та розширень на основі машинного навчання в майбутніх дослідженнях.

Ключові слова: симуляція тканини, геодезичні координати, проектування в реальному часі, параметричні моделі тіла, відповідність поверхонь, віртуальна примірка, деформація сітки