Enhance User Experience of PerfectFit by Resolving Penetrations in the Simulations

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I. Introduction and Motivations

Clothing is a vital element to our daily life. With the advancements of online shopping and manufacture, the uprising needs for more accessibility to virtual try-on with customization reveal a great commercial potential. Previous works in this topic usually focus on the customers' experience on fitting themselves in the fixed-shape products, but the new work in the lab, PerfectFit: Custom-Fit Garment Design in Augmented Reality [26], inspires me to explore the interaction method from a different perspective. In PerfectFit, the garments are manipulated and re-designed to fit individuals' physical attributes. Therefore, this new design lowers the barrier of customers' accessibility to stylish products. However, by inspecting the demo frame by frame, I realize there are some improvements can be made to the current phase of PerfectFit.

First, the cloth is not stable. During the demo, we can see the cloth is constantly trembling. Since there lacks the access to the codebase and more related details, I boldly infer the possible reason for this numerical instability might be the inconsistency of motion capture or a non-guaranteed penetration-free algorithm. However, since the cloth remains shaking at the same amplitude when the client role remains still and the incorrect force calculations at 0:44 in the video, I believe the observed instability is more likely to be the typical drawback of position based dynamics. If we can apply an efficient penetration-free simulator in PerfectFit, then it will be closer to an ideal tool in the working scenarios and offers better user experience. Besides, the layers and texture of the garments seems less diverse than expected in real-life situation. Previous works applying learning-based methods have better performance in fast rendering wraps and cloth deformation caused by changing poses. However, the recent methods implemented with real-time simulation are more powerful in handling different materials and objects due to the rigidity to physical laws. Since the combination of cloth is also important in both fashion industry and in our daily life, we can extend PerfectFit to meet broader needs of clothing. In my work, I argue the state-of-art simulator, subspace preconditioned PD-IPC [6], is able to resolve most of the problems in the simulation and implement coupling of other materials and physical effects in the future.

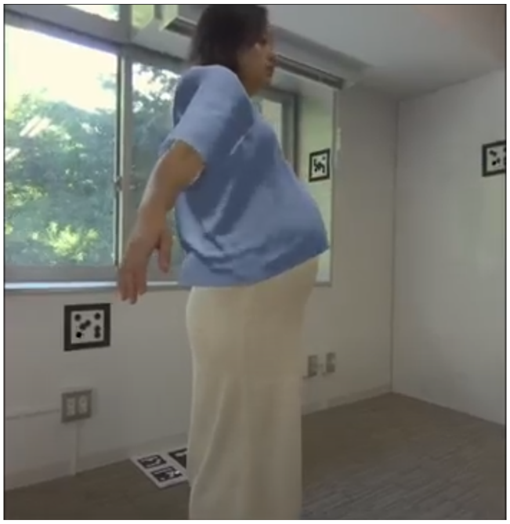

Fig. 1. The unnatural forces and trembling in the demo of PerfectFit

II. Related Works

A. Projective Dynamics

Physical-based cloth simulation has been popular in the realm of graphics community. Modern cloth simulation often endorses implicit time integration scheme pioneered by Baraff and Witkin. [1] Since this scheme will introduce extra damping, strain limiting is also used to counter this problem. Liu et al [2] introduced a new method to simulate the cloth with mass-spring model with implicit Euler and solve it as a energy minimization problem. This idea can be achieved by solving global/local steps alternatively and later is generalized by Bouaziz et al. as Projective Dynamics in their work. [3]

PD is an excellent framework for paralleling due to its design. In each solve, the global steps solve a fixed linear system and remain constant during the solving of local steps. And the local steps are required to solve the constraints inside the system separately in parallel. This alternating procedure continues until the energy converge within an arbitrary tolerance. In previous works, some techniques are applied to enhance the performance of PD such as using Cholesky factorization to precomputed system matrix, applying approximation in global solves by fast Jacobi iterations, and implementing Chebyshev acceleration techniques to accelerate convergence. [4] [5] Unfortunately, it is reported PD still requires a substantial number of iterations in high-resolution cloth simulation scenarios. [6]

But, PD is still one of the most suitable simulator for parallel and its variants work are proven decent with the contact models will be introduced in the following section. This GPU-friendly feature also unleashes its potential in differentiable simulations for system identification which will be in another topic I am going to discuss later.

B. Incremental Potential Contact

IPC [?] [31]is a computational approach based on idea of interior-point method. In 1992, Mehrotra incorporated barrier functions to approximate inequality constraints induced by collisions and contact. [29] And Li et al. validated the robustness and feasibility of barrier-based collision models and generalize their idea as Incremental Potential Contact. Traditional contact model in early works tend to formulate collisions as impulses [1] [30] [9]. Doing so will introduce inevitable stiffness to the simulations which requires huge workload on parameter tuning to eliminate undesired artifacts and ensure the convergence. And later, works on complementarity programming also failed in handling collisions in complex scenarios. Since the object is NP-hard, the searching always far more expensive than we can afford. [10] Another popular idea is penalty methods and repulse methods [3] [8] [11] [5] which are inexpensive. But still, they usually fail in larger time steps and intersections among models continuous to exist.

In IPC, the contacts are formulated by barrier function as a form of potential w.r.t. unsigned distance. It brings better robustness and smoothness to the simulation than those rely on signed distance methods and impulses. The barrier penalty function in IPC yields an increasing repulsion when colliding objects move closer and pushes them away before penetration happens. By this mean, interpenetration is avoided in each time step while the algorithm ensures the inequality constrains are constantly satisfied. The Continuous Collision Detection(CCD) is used in line search of IPC. It ensures the displacement update is well confined in domain of the barrier functions. Since CCD-based line search gives the direction for the simulation to continue, CCD is required in every iteration and it is the key element of IPC to keep penetration-free. It converts constrained simulation to unconstrained ones and therefore allows high-resolutions of collisions and contacts. However, since CCD is required in each iteration, it leads to high cost and unfriendliness to parallel. Follow-up works showed possible ways to conquer this challenge. Lan and colleagues [4]alleviated the efficiency issue by applying a inexact approximation to replace the Newton iteration [12] used in in original IPC on PD framework and further upgrade it by stencil-wise Newton-CG in their later work. [13]And most recent work by Li et al. formulates a new PD framework focus on subspace simulation and obtained 4x speed up over previous PD-IPC versions as well as a 10x acceleration over original IPC. By Li and colleagues [6], global steps of subspace-PD-IPC will solve for displacement field in subspace to capture low-frequency motion modes with pre-factorized global matrix. And the high frequency details are solved with Chebyshev-Jacobi relaxation [5] [14] on the full-order system. According to their performance report, this new scheme yields a suitable performance for real-time cloth simulation while maintaining penetration-free. [6] The details of the framework of this work will be discussed in the later section of my proposed method and will be the foundation of it.

Further works on IPC also validates the robustness of IPC in different scenarios such as co-dimensional simulation for thin membranes [21], penetration-free rigid body simulation [17], wrinkle simulation [20] and other materials and effects such as solid-fluid coupling, multi-bodies dynamics and adherent materials simulation. [18] [19] [22]. Now, IPC and its variants are still evolving rapidly with the core idea of keeping penetration-free while aiming for high speed in rich resolution.

C. Differentiable Cloth Simulation

Differentiable simulation has been an uprising topic in the intersection of computer graphics and machine learning. In differentiable simulation, gradients for initial states, system parameters and design parameters are used to approximate the desired states, usually future states of the system. By this mean, a new type of simulator suitable for real-time simulation and interactive applications seems to have great potential. Recently, there are encouraging breakthroughs in rigid-body dynamics [16] and soft-body dynamics [8] [?]. However, due to the higher requirements in resolution and rich contacts, the attempts for differentiable cloth simulation remain comparably sparse to other topics.

In 2022, Li et al. proposed DiffCloth, a new differentiable cloth simulator, based on dry frictional contact model [7] and embeds it to differentiable PD framework introduced by [15] In model of dry frictional contact, the contacts are assumed only happen to nodes. Therefore, Ly and colleagues [7] formulate the contacts in three situations respectively which are take-off, stick and slip. Li et al. implement this idea in their implicit time integration and further calculate the gradients of velocities. Their gradient-based method and backpropagation are an enhanced version of the work by Du et al. which focus on rigid body with low frequency of contacts and over-simplified frictions. [15] DiffCloth shows strong capability in solving multiple tasks like trajectory prediction and system identification. [24]. DiffCloth is a great success to simulate frictional contact events in cloth, but the work the Yu et al. [17] still shows it fail to strictly avoid undesired artifacts and penetrations. And in their work, Yu et al. claim a decent combination of IPC and DiffCloth and create a new differentiable simulator to solve intersection-free friction contact and two-way coupling with articulated rigid bodies. But, since IPC and its latest variants are still suffering from high computational costs, I think the combination of IPC and differentiable simulation require further research.

In December 2023, Li et al. introduced their new work after DiffCloth, namely DiffAvatar. [27] This work presents a new downstream application of differentiable cloth simulation. DiffAvatar utilizes differentiable simulation to generate physically plausible assets that can be used for simulation applications. In

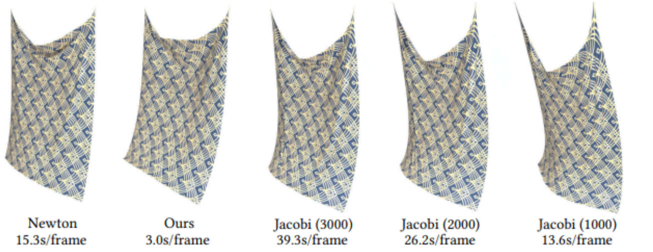

Fig. 2. A comparison between subspace PD-IPC with Chebyshev-Accelerated Jacobi-PD by Wang[2015]. (250K vertices and 500K triangles) [6]

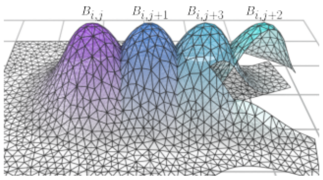

Fig. 3. The illustration of how subspace is built. [6]

their work, DiffAvatar uses scanned body information and 2D garments data successfully build a realistic cloth animation on the avatar with different poses. [27] Different from PerfectFit, DiffAvatar solely focus on the scene recovery from real-time gathered data; while PerfectFit emphasizes the mechanism of interaction between virtual garments and designer. However, I think it is a outstanding example for the implementation of differentiable cloth simulation.

III. Proposed Method

My idea is largely constructed upon the subspace-PD-IPC. [6] Therefore, it is helpful to follow framework of this work.

A. *Construction of Subspace*

Subspace simulation is a new idea for IPC and its variant. It is built upon Reduced-Order Modeling and aimed to reduce the critical degrees of freedoms to speedup the simulation. In order to do so, first clothing items are treated as several flat fabric pieces connected with stitches rather than a whole piece of fabric. So, the cloth is defined as $\Omega = \cup_{i=1}^{k} \Omega_k$ where Ω stands for the domain of patches for 1 to k. Next, Li and colleagues embed the cloth domain onto a 2D Cartesian grid and apply Material Point Method quadratic spline shape functions on the grid points as following. [6]

$$B_{ij}(X) = N(u/\Delta x - i)N(v/\Delta x - j) \tag{1}$$

$$N(x) = \begin{cases} \frac{3}{4} - x^2, & |x| < \frac{1}{2}, \\ \frac{1}{2}\left(\frac{3}{2} - |x|\right)^2, & \frac{1}{2} \leq |x| < \frac{3}{2}, \\ 0, & \frac{3}{2} \leq |x|. \end{cases} \tag{2}$$

where (i,j) denotes the grid index, u and v represent the parameterization of X, Δx correspond to spline's kernel size and the spacing of the 2D grid. By this mean, ambient space of Ω is decomposed as $\mathcal{P} = \mathcal{B} \otimes I_3 \in \mathbb{R}^{3M \times 3N}$ which means space basis matrix $\mathcal{P}$ is represented by Kronecker product between spline basis $\mathcal{B}$ and 3D identity matrix where M is the number of bases and N is number of vertices. Now, the states in subspace with given reference position x_0 is expressed as $\left\{x : x = x_0 + \mathcal{P}y, y \in \mathbb{R}^{3M}\right\}$

B. *Subspace Projective Dynamics*

By [6], they sketch the global step upon the optimization time integration outlined by [23]which leads to solving a linear system with fixed system matrix $\boldsymbol{H} = \frac{1}{\boldsymbol{h}^2}\boldsymbol{M} + \boldsymbol{K}_{\text{mem}} + \boldsymbol{K}_{\text{bend}}$,where $\boldsymbol{K}_{\text{mem}}$, $\boldsymbol{K}_{\text{bend}}$ stand for membrane energy Hessian and bending energy Hessian at the rest shape. More specifically, the global solve will focus on solving $\boldsymbol{H}u = b$ where u is the displacement increment respect to previous global step. By restricting the displacement to the form $u = \mathcal{P}y$, we can obtain a reduce-order global system as

$$\mathcal{P}^\top \boldsymbol{H} \mathcal{P} y = \mathcal{P}^\top \boldsymbol{b}. \tag{3}$$

and therefore $\hat{H} = \mathcal{P}^\top \boldsymbol{H} \mathcal{P}$ as reduced global system matrix with a dimension corresponding to the number of bases in $\mathcal{P}$.

C. *Contacts*

As mentioned in previous section, the contacts in IPC is handled by barrier-based method. The contact proxy in subspace PD-IPC is defined as

$$\hat{B}\left(x; x^*\right) = B(x) + \nabla B\left(x^*\right)^\top \left(x - x^*\right) + \frac{1}{2}\left\|x - x^*\right\|^2_{\nabla^2 B(x^*)}. \tag{4}$$

where x^* is the initial state and $B(x)$ is barrier potential function defined as

$$B(x) = \sum_{P,T} b(\operatorname{dist}(P,T)) + \sum_{E_1,E_2} b\left(\operatorname{dist}\left(E_1, E_2\right)\right) \tag{5}$$

and

$$b(d) = \begin{cases} -(d - \hat{d})^2 \log(d/\hat{d}), & 0 < d < \hat{d}, \\ 0, & d \geq \hat{d}. \end{cases} \tag{6}$$

Here, d and dist are the calculated distance between objects, (P,T) represents an point-triangle part and (E_1,E_2) represents an edge-edge pair. The computation details can be found in supplementary of IPC by Li et al. [**?**]

Therefore, the subspace global matrix based on (3) with contacts will be

$$\mathcal{P}^\top \left(\boldsymbol{H} + \nabla^2 B\left(x^*\right)\right) \mathcal{P} = \mathcal{P}^\top \boldsymbol{H} \mathcal{P}^\top + \mathcal{P}^\top \nabla^2 B\left(x^*\right) \mathcal{P}^\top \tag{7}$$

Since the global system is subject to constant changes, Li and colleagues endorse BFGS iterations to reuse the global system matrix in non-contact situation. The details of utilization and tuning of BFGS iteration can be find in their work.[Li et al. 2023] Other-than BFGS, the Jacobi iteration is also used in solving global steps on full order.

Since PD solver will provide a trial solution containing penetrations, Li et al. suggest to performe penetration correction by following energy minimization. This step can be helped with Newton-PCG.

$$\frac{1}{2h^2}\left\|x - x^{\text{tr}}\right\|^2_M + B(x). \tag{8}$$

Fig. 4. A high-resolution(more than 120k) simulation carried out by subspace IPC which is strictly non-penetration. The average cost is 23s per frame. [6]

where x^{tr} denotes the trail solution.

In conclusion, subspace-PD-IPC has an algorithm as following: And in order to fuse it into PerfectFit, we can sketch an algorithm based on Algorithm 1.

Algorithm 1 Subspace PD-IPC

```
if it is the first time step then
    Construct subspace basis sparse matrix. $\mathcal{P}$.    ▷ Section III.A
    Factorize the global matrix $\mathcal{P}^\top \boldsymbol{H}\mathcal{P}$ . ▷ (3)
end if
Update prediction position. $\hat{x}$
Run global step w.o. contact at $\hat{x}$
Construct contact proxy. ▷ Section III.C
Initialize BFGS history.
while not converged do
    Run 2 iterations of subspace BFGS.
    Run 5 iterations of Jacobi on full order.
    Local steps solved in parallel.
end while
Run penetration correction step. ▷ Section III.C
```

Algorithm 2 Proposed Algorithm

```
if Garment is modified then
    Read and build meshes
    Construct new subspace and update basis sparse matrix $\mathcal{P}$ based on current states
    Run Algorithm 1
end if
Update meshes w.r.t. motions of clients
Run Algorithm 1
```

D. A brief of DiffAvatar

The pipeline of DiffAvatar consists of three major parts which are preprocessing, forward computation and backward propagation.

1) Preprocessing: Like in PerfectFit, DiffAvatar also uses visual data as input. The visual data is generated by a multi-view capture and used to establish the initial pose and shape of parametric body model.

Garments and body models. Garments in DiffAvatar are stored in 2D pattern space at their rest states and modeled as sewn-up triangle meshes in 3D. The body model is combined with the skeleton and the shape information. The skeleton is described with parameter P generated by joint angles ψ and bone lengths with local transformation; the shape is encoded by the statistical shape coefficient ν as $V_0 + \nu V$, where V_0 and V encode average body shape and shape basis function respectively. The overall representation of body shape S can be abstracted as following. [27]

$$S = \mathbb{R}^{3\times V_b} \times \mathbb{R}^{P} \rightarrow \mathbb{R}^{3\times V_b} \tag{9}$$

Initialization. In initialization part, Li and her colleagues process multi-view images to reconstruct and segment a 3D scan to initialize the shape and pose of body model. The garment of interest is chosen within the garment class produced by cloth segmentation algorithm ran on each of the cameras. The consistency of the garment class is enforced by selecting the garment classes appear in majority of the cameras. [27]

2) Forward computation: In differentiable simulation, the forward computation usually is the simulation from time step n to $n+1$. So is in DiffAvatar.

Cloth simulation. Due to the consideration of efficiency, Li et al. choose XPBD as their simulation model. The update steps is sketched as following. [26]

$$\mathrm{x}_{n+1} = \mathrm{x}_n + \triangle\mathrm{x}_C + \triangle t(\mathrm{v}_n + \triangle t\mathrm{M}^{-1}\mathrm{f}_{ext}) \tag{10}$$

in which x_n stands for vertices coordinate at time step n; $\triangle\mathrm{x}_C$ is the sum up displacement after solve constraints in triangle, dihedral, cloth-body collision, cloth-cloth collision.; v_n is the velocity at time step n; M is the mass matrix and f_{ext} is external forces. Furthermore, the velocity at time step $n+1$ in DiffAvatar is updated as

$$\mathrm{v}_{n+1} = \frac{1}{\triangle t}(\mathrm{x}_{n+1} - \mathrm{x}_n) \tag{11}$$

3) Backward propagation and optimizations: The efficient computation of gradient information of θ is the key part of differentiable simulation. In DiffAvatar, the backpropagation is described as the minimization of the gradient of goal function ϕ to θ, where θ is the control parameter vector. The computation of gradient is sketched as following, the details of it is presented in the previous work DiffXPBD. [27] [28]

$$\frac{d\phi}{d\theta} = \frac{\partial\phi}{\partial Q}\frac{dQ}{d\theta} + \frac{\partial\phi}{\partial\theta} \tag{12}$$

where Q is a sequence containing arbitrary number of previous states and current state. In DiffXPBD and DiffAvatar, (12) is optimized by a replacement of Q with a adjoint state set *Q'*. However, the underlying logic are the same. This optimization only influences the efficiency of the computation. [28]

Now, how to form the parameters θ and ψ is the main issue in this part. DiffAvatar divides the optimization into three categories: body shape and pose optimization, garment pattern optimization and material property estimation. Therefore, the parameters should include the body shape coefficient ν and pose(joint angle parameter mentioned above) coefficient ψ, the control cage coefficient ζ and the material parameter λ. ζ is very important. ζ is a set of vertices on the boundary of 2D garment, and they are chosen to control the deformation and

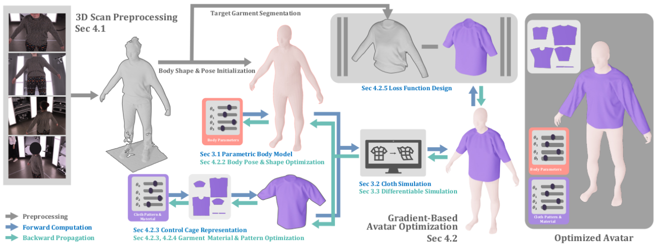
3D Scan Preprocessing
Sec 4.1
Target Garment Segmentation
Body Shape & Pose Initialization
Sec 4.2.5 Loss Function Design
θ_0
θ_1
θ_2
θ_3
Body Parameters
Sec 3.1 Parametric Body Model
Sec 4.2.2 Body Pose & Shape Optimization
Sec 3.2 Cloth Simulation
Sec 3.3 Differentiable Simulation
Cloth Pattern & Material
Sec 4.2.3 Control Cage Representation
Sec 4.2.3, 4.2.4 Garment Material & Pattern Optimization
Gradient-Based
Avatar Optimization
Sec 4.2
Optimized Avatar
Preprocessing
Forward Computation
Backward Propagation

Fig. 5. Pipeline of DiffAvatar. I believe it will help the understanding. [26]

manipulation of 2D patterns. Li et al. emphasize ζ prevents ill-shaped or non-physical inverted rest shape geometries from failing the simulation and also avoid the optimization stuck in local minimum. [26] The other two parameters can be explained by their names. Therefore, $\frac{dQ}{d\theta}$ in (12) can be solved as the sum of the respective derivatives of the displacements of resolving cloth-body collision, triangle constraints, dihedral constraints to parameters in θ. [26]

The goal function ψ is also called loss function. In DiffAvatar, the loss function is formed by feature matching and regularization. Feature matching is aimed to show how well garment matches the scanned data. It is unified by two loss, namely the boundary loss and the interior loss. Boundary loss is to measure if garment is overlapping well enough and interior loss matches the looseness of the fit; as for regularization loss, it is a measure of how well the patterns are maintained during the fitting. [26]

4) Summary for DiffAvatar: Li et al. claim DiffAvatar is so far the SOTA algorithm in scene recovery for cloth simulation. [26] The reason I mention this work in my proposal is not for direct implementation of DiffAvatar in PerfectFit. I think it offers a totally different perspective to cope with the issue in PerfectFit. In the first part of my proposal, I attempt to solve the problem by replacing the simulation model while DiffAvatar inspires me to focus more on generating a better assets before utilization of them in the further applications.

IV. Summary

In this proposal, I manage to propose a method to optimize the PerfectFit from simulation perspective. I believe IPC and its variants are suitable for the time-sensitive and interactive cloth simulations since the realistic visual effects and diverse materials choices will surely improve the experience for both designers and customers. And I will continue to focus on the advancements in real-time simulation and apply it to more interactive scenarios.

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