

Augmented Mass-Spring Model for Real-Time Dense Hair Simulation

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Figure 1. Our AMS model for dense hair simulation is capable of handling complex settings with a large number of strands, efficiently simulating scenarios such as hair under wind (left, 14, 718 strands at 67 FPS), hair-face contact (middle, 7, 528 strands at 156 FPS), and hair interacting with complex objects (right, 10, 298 strands at 114 FPS), all in real time.

Abstract

We propose a novel Augmented Mass-Spring (AMS) model for real-time simulation of dense hair at the strand level. Our approach considers the traditional edge, bending, and torsional degrees of freedom in mass-spring systems, but incorporates an additional one-way biphasic coupling with a ghost rest-shape configuration. Through multiple evaluation experiments with varied dynamical settings, we show that AMS improves the stability of the simulation in comparison to mass-spring discretizations, preserves global features, and enables the simulation of non-Hookean effects. Using a heptadiagonal decomposition of the resulting matrix, our approach provides the efficiency advantages of

mass-spring systems over more complex constitutive hair models, while enabling a more robust simulation of multiple strand configurations. Finally, our results demonstrate that our framework enables the generation, complex interactivity, and editing of simulation-ready dense hair assets in real time.

1. Introduction

Hair dynamics play a crucial role in enhancing the visual realism of digital characters. However, simulating hair remains one of the most challenging and resource-intensive tasks, due to its thin, flexible structure, the interactions be-

tween strands (including friction and collisions with both the body and other hair strands), and the sheer volume of hair, which can range from 100,000 to 200,000 strands on a single head. Over the years, various techniques have been developed to replicate hair dynamics, including sophisticated models like the Discrete Elastic Rods (DER) approach [1]. However, due to the high computational demands, simulations using physics-based models are typically limited to hundreds of strands for low-latency applications, which restricts their uses in games and animation. To achieve interactive performance, many systems simulate a smaller number of guide strands and apply linear or neural interpolation techniques to upsample the strand count in real time. While this approach improves performance, it often sacrifices fidelity, particularly in areas with complex strand collisions.

In recent efforts to simulate a larger number of strands in real time, more efficient integration routines [4] that parallelize DER-based physics models have emerged, alongside data-driven methods using neural networks to predict hair dynamics. However, these methods face robustness issues in handling outlier shapes and dynamic settings and dealing with complex interactive scenes and intricate hairstyles. In this paper, we propose a novel Augmented Mass-Spring (AMS) model for real-time dense hair simulation. Standard Mass-Spring (MS) model [9] is methodologically simpler and computationally cheaper than Discrete Elastic Rod (DER) models or neural-based methods. However, by design, the MS model struggles to capture global strand behavior, leading to issues such as instability, excessive sagging, and a loss of hair structure during simulation. To address these limitations, we introduce several key augmentations to the MS model. For improving the stability of the system and encoding global strand features, we design a novel but simple scheme. We incorporate one-way biphasic interactions, combined with a ghost rest-shape, applied to the particles along the hair strands (Figure 3). This approach stabilizes the simulation while preserving global structural integrity. To maintain the dynamic realism and computational efficiency of MS models, we design a two-stage hybrid Eulerian/Lagrangian scheme that integrates fluid system and particle system to handle hair interactions. This combination allows us to simulate intricate hair behavior without sacrificing performance.

We evaluate our framework through comparative experiments across various dynamic and interaction settings, and additionally showcase **strand-level interactive simulations and grooming of dense hair** on a consumer-grade computer, utilizing less than 1 gigabytes of GPU memory. To the best of our knowledge, AMS is the first framework to enable real-time simulation of a wide range of hair and facial hair styles, including curly hair, asymmetrical styles, and ponytails, while having the capability of capturing **fine**



Figure 2. Integrating video-based facial tracking [5] with our real-time hair simulation enables the control of digital avatars with dynamic and coherent hair motion.

collision details when interacting with complex geometries (Figure 1) and **handling extreme forces**, such as those encountered during intense motion, like on a roller coaster (Figure 10). Furthermore, by integrating video-based facial tracking with our real-time hair simulation, we enable the control of digital avatars with dynamic and coherent hair motion (Figure 2).

2. Related Work

Here we discuss the physics-based hair simulation model and the recently emerged neural-based approaches.

2.1. Physics-based Approaches

Physics-based hair simulation methods vary in the geometric and constitutive models they use to simulate either individual hair strands or clumps of hair. Approximating hair as large bundles has been explored through various techniques, including cubic lattice representations [23], volumetric models [11, 27], and 2D strips [10]. While these approaches are typically very efficient, they are limited in their ability to capture effects and interactions that require modeling at the level of individual strands. In contrast, individual hair strands have been modeled using mass-spring systems [17] and multi-body chains [3]. Some approaches, such as the use of lattice deformers with additional springs [19], enhance system stability, while others focus on efficient solvers and improved hair-body interactions [9].

More physically accurate and complex models, such as the super-helix scheme [2], DER [1], and exponential time integrators [15, 16], provide greater realism but at the cost of significantly higher computational demands. Recently, Daviet *et al.* [4] made significant engineering advancements to accelerate the DER model by parallelizing strand computations, enabling the simulation of over 10,000 guide strands in real time. This approach significantly improves the fidelity of real-time hair simulation. However, despite

these optimizations, DER-based methods remain computationally complex for simulating strand dynamics, making them challenging to apply in more intricate interactive scenarios with complex hairstyles. Additionally, these methods require specialized integration routines to address sagging artifacts [7].

In this context, we propose AMS as an evolution of traditional mass-spring schemes, enabling more robust and diverse hair dynamics simulations. This approach improves the fidelity of mass-spring-based hair simulations while preserving the efficiency advantages of these models.

2.2. Neural-based Approaches

With the rise of machine learning in physics, recent research has begun exploring neural approaches to predict hair dynamics using data generated by physics simulators, with the aim of accelerating animation. One line of work focuses on predicting individual hair strand shapes based on gravity direction and head pose [30]. Another approach uses deep learning to add fine details to interpolated dense hair from sparse guide strands [13, 20]. More recently, Quaffure [22] introduced a real-time neural framework for quasi-static hair simulation that achieves plausible dynamic responses via a self-supervised loss. Additional efforts explore vision-based reconstruction hair, such as HairStep [29], which introduces an intermediate representation consisting of a strand map and depth map, and the two-stage method of Neural Haircut [21], where coarse geometry is first recovered using volumetric representations, followed by strand-level refinement. Further advances, like NeuWigs [25], leverages a 3D volumetric autoencoder for hair capture and animation, while MonoHair [28] separates hair modeling into exterior and interior geometries to achieve high-fidelity hair reconstruction from a monocular video.

While these methods can achieve real-time results, they are heavily dependent on the distribution of the training data, limiting their applicability to the data’s domain. Consequently, these models may struggle in scenarios outside their training data, leading to gaps in performance when faced with unfamiliar cases. In practice, it is infeasible to generate training data that covers all possible scenarios, given the vast combinations of internal parameters, external forces, and collision situations. Furthermore, the grooms produced by these methods lack embedded dynamic information, causing their behavior to potentially deviate significantly from the original intent during motion. In contrast, digital grooming within our dense hair simulation framework adheres to physical constraints even for manipulated strands, ensuring that the final groom will exhibit predictable dynamic behavior and handling complex hair-solid interactions.

3. Formulation

In this section, we introduce our augmented mass-spring formulation, and describe how we handle hair-hair and hair-solid interactions.

3.1. Augmented Mass-Spring Model

In a general MS scheme, each hair strand is discretized into particles connected by springs, providing edge, bending, and torsion degrees of freedom. However, issues such as ill-defined torsion springs and collapsed tetrahedra can arise when consecutive particles become degenerate. To address these challenges, Selle *et al.* [19] introduced strongly coupled ghost particles and *altitude* springs (Figure 3, middle), improving stability. However, this model relies on highly stiff springs to maintain local features and minimize jittering, which in turn introduces numerical divergence and limits the simulation time step size [26]. Furthermore, the purely local connectivity of the spring system leads to significant sagging at initialization and a loss of global hair structure.

To overcome these limitations, we introduce two weakly coupled interactions in our MS formulation (Figure 3, right). First, an *angular* interaction to ensure nondegenerate tetrahedra by applying forces that prevent excessive collapse of consecutive particles. Second, an *integrity* interaction that couples each particle to its corresponding ghost based on the total strand displacement, counteracting sagging and preserving the overall hair shape. This mechanism maintains global features independently of discretization density by offsetting the accumulated weight of particles. Moreover, to ensure these additional forces do not over-influence the system and decrease the simulation fidelity, we set their coupling constants several orders of magnitude lower than those of traditional local springs. A more detailed motivation is provided in our supplementary material.

3.1.1. Model Description

We consider the basic edge, bending, and torsion springs, for which a uniform spring constant κ_L is used, as well as a weakly interaction with a ghost rest-shape via one-way springs that connect each particle with their corresponding ghost in the rest configuration, as demonstrated in Figure 3, right. Moreover, in general, MS needs $2N - 1$ coupled particles, while AMS uses only the original N particles. This difference between models makes AMS more efficient in terms of memory, as only a matrix with half the size of that in MS is needed to solve during each iteration.

3.1.2. Biphasic Interaction

Given a discretized strand containing n particles with positions $\mathbf{x}_0, \dots, \mathbf{x}_{n-1}$, we define $\mathbf{y}_i$ to be the position of the ghost corresponding to the $i - th$ particle. The first part of

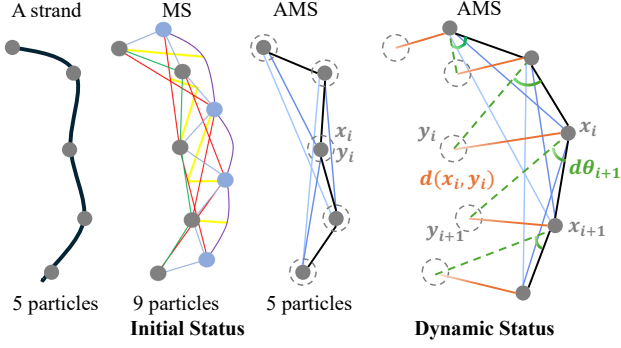


Figure 3. Schematic of a hair strand: initially discretized with particles (left); built as MS (middle) with edge (green), bending (blue), torsion (red), ghost (blue/purple), and altitude (yellow) springs; and as our AMS (right), using a ghost rest-shape (dotted circles) and one-way biphasic springs (purple outline). MS requires $2N-1$ coupled particles; AMS only uses N . Right: deviations from rest-shape are handled via integrity springs (κ_I) based on point distance, and angular springs (κ_α) based on angle distance $d\theta$, forming biphasic links to the ghost.

the interaction uses an *integrity* spring with zero rest length and tension T_I computed as

$$T_I = \kappa_I d(\mathbf{x}_i, \mathbf{y}_i), \quad (1)$$

where κ_I is the spring constant, and $d: \mathbb{R}^3 \times \mathbb{R}^3 \rightarrow \mathbb{R}^3$ is the distance function between two vectors. This spring connects each particle to its corresponding ghost configuration. Moreover, note that, at initialization, $\mathbf{x}_i = \mathbf{y}_i, \forall i \in \{1, \dots, n\}$. We also introduce an *angular* spring, so that, if $d\theta_{i+1}$ is the angle between segments $\mathbf{x}_i \mathbf{y}_{i+1}$ and $\mathbf{x}_i \mathbf{x}_{i+1}$, then the tension of the spring T_α is given by

$$T_\alpha = \kappa_\alpha d\theta_{i+1}, \quad (2)$$

where the spring connects the $(i+1)$ th particle to its ghost. At initialization, all the edges are aligned to the ghost counterpart, so that $d\theta_{i+1} = 0 \forall i \in \{1, \dots, n\}$. Each pair of springs between ghost and real particles act in a biphasic fashion, *i.e.*, they are connected in parallel.

3.1.3. Linearization

We proceed as before, letting $\mathbf{x}_i^n, \mathbf{y}_i^n, \mathbf{v}_i^n$, and $\mathbf{w}_i^n$ denote, respectively, the position of each ghost-real pair, and their correspondent velocities. The superscripts denote the current time step. Furthermore, the vectors $\mathbf{X}^n, \mathbf{Y}^n, \mathbf{V}^n, \mathbf{W}^n \in \mathbb{R}^{3N}$ hold the position and velocities of the complete ghost-real strand pair. Using this notation, the backward Euler equations from time t^n to t^{n+1} can be written as

$$\mathbf{X}^{n+1} = \mathbf{X}^n + \Delta t \mathbf{V}^{n+1}, \quad (3)$$

$$\mathbf{V}^{n+1} = \mathbf{V}^n + \Delta t \mathbf{M}^{-1} (\mathbf{F}^n + \mathbf{S}^{n+1} - \mathbf{G} \mathbf{V}^{n+1}), \quad (4)$$

where $\Delta t = t^{n+1} - t^n$, $\mathbf{M}, \mathbf{G} \in \mathbb{R}^{3N \times 3N}$ are the mass and damping coefficient matrix, respectively; the matrices $\mathbf{F}^n, \mathbf{S}^{n+1} \in \mathbb{R}^{3N \times 3N}$, on the other hand, denote the total external and internal forces. In particular, each entry s_i^{n+1} of $\mathbf{S}^{n+1}$ is computed as

$$s_i^{n+1} = \sum_{j \in \mathcal{N}(i)} \kappa_{i,j} \left((\mathbf{x}_j^{n+1} - \mathbf{x}_i^{n+1})^\top \hat{\mathbf{d}}_{i,j}^{n+1} - l_{i,j} \right) \hat{\mathbf{d}}_{i,j}^{n+1},$$

where the stiffness $\kappa_{i,j}$ and rest-length $l_{i,j}$ characterize the spring connecting particles i and j , the set $\mathcal{N}$ contains all particles connected to i , and the direction vector is computed as

$$\hat{\mathbf{d}}_{i,j}^{n+1} = \frac{\mathbf{x}_j^{n+1} - \mathbf{x}_i^{n+1}}{\|\mathbf{x}_j^{n+1} - \mathbf{x}_i^{n+1}\|}.$$

We follow the linearization proposed by Selle *et al.* [19], where the direction vector is kept fixed so that $\hat{\mathbf{d}}^{n+1} \rightarrow \hat{\mathbf{d}}^n$, and the internal force terms become

$$\begin{aligned} s_i^{n+1} = & \sum_{j \in \mathcal{N}(i)} \kappa_{i,j} (\|\mathbf{x}_j^n - \mathbf{x}_i^n\| - l_{i,j}) \hat{\mathbf{d}}_{i,j}^n \quad (5) \\ & + \sum_{j \in \mathcal{N}(i)} \kappa_{i,j} \Delta t \mathbf{D}_{i,j}^n (\mathbf{v}_j^{n+1} - \mathbf{v}_i^{n+1}), \end{aligned}$$

where $\mathbf{D}_{i,j}^n = (\hat{\mathbf{d}}^n)^\top \hat{\mathbf{d}}^n$ is the direction matrix for particles i and j . The first term in this expansion corresponds to the explicitly integrated elastic force, while the second term describes the damping of the spring, fixed at $\kappa_{i,j} \Delta t$, to ensure stability in this semi-implicit discretization.

3.1.4. Integration

Given the expansion in Eq. (5), we can write the internal force vector as

$$\mathbf{S}^{n+1} = \hat{\mathbf{S}}^n + \Delta t \mathbf{C}^n \mathbf{V}^{n+1}, \quad (6)$$

where $\hat{\mathbf{S}}^n$ is the elastic term at $t = n$, and the connectivity matrix $\mathbf{C}^n \in \mathbb{R}^{3N \times 3N}$ is composed of block matrices $\mathbf{c}^n \in \mathbb{R}^{3 \times 3}$, computed as

$$\mathbf{c}_{ij}^n = \begin{cases} \kappa_{i,j} \mathbf{D}_{i,j}^n, & j \in \mathcal{N}(i), \\ -\sum_{j \in \mathcal{N}(i)} \kappa_{i,j} \mathbf{D}_{i,j}^n, & i = j, \\ \mathbf{0} \in \mathbb{R}^{3 \times 3}, & \text{else.} \end{cases} \quad (7)$$

Note that, since our rigid-body ghost configuration is one-way coupled with the real particles, we can include the ghost interaction directly in the elastic term $\hat{\mathbf{S}}^n$, as well as by adding the velocity term separated as the external interaction $\kappa_\tau \Delta t \mathbf{D}_{g,i}^n \mathbf{w}_i^{n+1}$, and the damping $-\kappa_\tau \mathbf{D}_{g,i}^n \mathbf{v}_i^{n+1}$, where κ_τ is a dummy index for the *integrity* κ_I and *angular* κ_α spring constants, and the ghost direction matrix $\mathbf{D}_{g,i}^n$ is defined as

$$\mathbf{D}_{g,i}^n = \begin{cases} (\hat{\mathbf{d}}_{g,i}^n)^\top \hat{\mathbf{d}}_{g,i}^n & \|\mathbf{x}_i^n - \mathbf{y}_i^n\| \neq 0, \\ \mathbf{0} \in \mathbb{R}^{3 \times 3} & \text{else.} \end{cases} \quad (8)$$

This separation of ghost terms allows to compute first the ghost rigid-body dynamics and then update the real strand dynamics using an $N \times N$ matrix, as opposed to an $(2N - 1) \times (2N - 1)$ matrix in a two-way coupled system. Combining all the interaction terms, we can express the implicit Euler step $\mathcal{E}$ as

$$(I + \Delta t M^{-1} G - \Delta t^2 M^{-1} C^n) \mathbf{V}^{n+1} = \mathbf{V}^n + \Delta t M^{-1} (\mathbf{F}^n + \hat{\mathbf{S}}^n). \quad (9)$$

3.2. Hair Interactions

We implement a two-stage hybrid Eulerian/Lagrangian approach, resembling that of [14]. In the first stage, we rasterize hair segments into a dynamic background Eulerian volume that moves rigidly with the mesh (as opposed to the static volume formulation of McAdams *et al.* [14]), and solve the equivalent fluid system using a FLIP/PIC scheme. Then, we transfer the resulting velocity back to the particles, effectively preconditioning the velocity vector, and resolve detailed Lagrangian collisions in a second stage.

3.3. Hair-Solid Collisions

The last step of an iteration corresponds to final velocity and position corrections to account for solid collision response. Having a pre-computed SDF $\sigma_{\text{head}} : \mathcal{R}^3 \rightarrow \mathcal{R}$ of the head, with an associated velocity field $\mathbf{v}_{\text{head}} : \mathcal{R}^3 \rightarrow \mathcal{R}^3$, we first check for particles that will be updated into an invalid position $\sigma_{\text{head}}(\mathbf{x} + \Delta t \mathbf{v}) < 0$. For these cases, we first update the velocity by

$$\mathbf{v}' = \mathbf{v}_{\text{head}} + \max \left(0, 1 - \mu \frac{\|\mathbf{v}_N - \mathbf{v}_{\text{head}_N}\|}{\|\mathbf{v}_T - \mathbf{v}_{\text{head}_T}\|} \right) (\mathbf{v}_T - \mathbf{v}_{\text{head}_T}),$$

where $\mathbf{v}_{\text{head}} = \mathbf{v}_{\text{head}}(\mathbf{x} + \Delta t \mathbf{v})$, and the sub-indices N and T denote the normal and tangential components of velocities when projected on the level-set normal $\nabla \sigma_{\text{head}}(\mathbf{x} + \Delta t \mathbf{v})$. When the targeted positions of particles are still inside of the head, we pushed them further in a second stage by setting

$$\mathbf{x}' = \mathbf{x} + \left(\frac{\nabla \sigma_{\text{head}}}{\|\nabla \sigma_{\text{head}}\|} \sigma_{\text{head}} \right) (\mathbf{x} + \Delta t \mathbf{v}'). \quad (10)$$

4. Experiments

Our numerical procedure, including matrix decomposition and time integration scheme, is detailed in supplementary material. We present a variety of results simulated with our C++/CUDA framework, implemented as described in the previous section.

Table 1 provides an overview of the different experiments presented throughout this section, including the values of relevant parameters. The computation times listed in Table 1 are measured on an up-to-date desktop computer running our simulation framework on a NVIDIA GeForce

Table 1. Overview of the relevant parameters used in the scenes presented in this paper. Time T is listed in ms. Unless otherwise mentioned, identical parameter values of $[\kappa_L] = 10^6 \text{ N m}^{-1}$, $[\kappa_I] = 10^2 \text{ N m}^{-1}$, $[\kappa_\alpha] = 10^2 \text{ N rad}^{-1}$ are used in all simulations. We used a grid resolution of 128^3 for Eulerian computations. Peak GB for our largest asset was 0.58.

Fig.	Scene	# Strands	# Particles	T
4	Single Strand	1	30	0.01
5	Wisp Comparison	480	14k	0.02
6	Wig	10,422	214k	1.9
7	Hand Interaction	15,000	450k	15.2
8	Hollow Sphere	10,298	308k	1.8
1	Wind	14,718	294k	14.9
1	Asymmetric Style	7,528	150k	6.4
9	Beard	1,100	22k	0.03
10	Roller-Coaster	7,500	225k	7.4
11	Digital Grooming	7,905	166k	6.2

GTX 3080 Ti GPU. Unless otherwise mentioned, the assets we used were generated using the parametric hair model of [6].

4.1. Ablation Studies

We first study the impact of the biphasic interaction terms in our augmented mass-spring formulation.

4.1.1. Global Features

In Figure 4, we present the results for a single strand simulated with $\kappa_\alpha = 0 \text{ Nrad}^{-1}$ in AMS, alongside simulations using MS with increasing spring tensions. Despite the local tensions being orders of magnitude higher in MS, the strand loses its shape at initialization, and, for even greater tensions, the system becomes unstable. In contrast, the *integrity* tension T_I in our formulation effectively prevents the loss of global features by directly coupling the dynamic particles to the ghost rest configuration.

4.1.2. System Stability

In Figure 5, we assess the impact of the *angular* tension T_α in AMS by simulating a wisp of hair with our framework using $\kappa_L = 10^6 \text{ Nm}^{-1}$, $\kappa_I = 0 \text{ Nm}^{-1}$, and decreasing values of κ_α . The additional degree of freedom introduced by the *angular* term in our formulation enhances the stability of the system, allowing for the use of lower spring tensions and, consequently, higher time step sizes. This improvement enables real-time execution without compromising stability.

4.1.3. Simulation Fidelity

To compare the simulation fidelity with the advanced hybrid Cosserat-MPM model [7], we use the same real-world captured Wig model [12] and set up a similar wind condition, running on comparable hardware, since the original

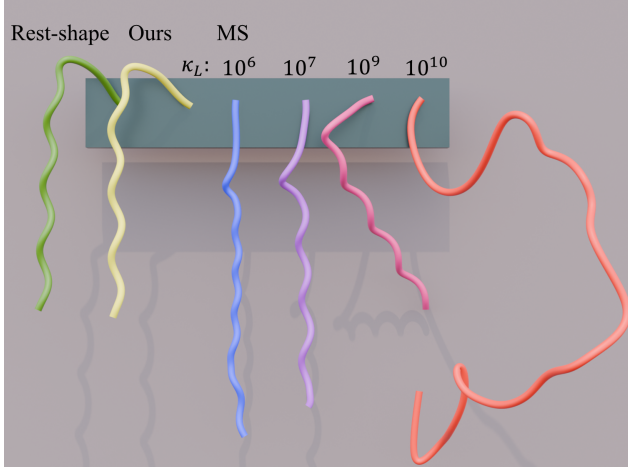


Figure 4. Simulated rest-shape of a single strand using our model and MS. Starting from a given configuration, our method preserves the global features by setting $\kappa_L = 10^7 \text{ Nm}^{-1}$, $\kappa_\alpha = 0 \text{ Nrad}^{-1}$, and $\kappa_I = 10^2 \text{ Nm}^{-1}$, while in MS, the shape is not maintained even as κ_L increases, eventually leading to instability.



Figure 5. Wisp simulation generated using our framework, showing progressively decreasing values of the *angular* coupling. As κ_α decreases, the simulation becomes increasingly unstable, ultimately collapsing at $\kappa_\alpha = 0$, where our system is equivalent to MS.

paper has not released its code. As shown in Figure 6, [7] simulates 1024 hair strands with a reported simulation time of 1.2 ms per frame, while our approach requires only 0.04 ms for the same number of strands. For higher fidelity, we increase the number of simulated strands to 10,422 (full asset), with a per-frame time of just 1.9 ms. Additionally, while [7] requires specific optimizations during initialization to alleviate sagging artifacts, our approach eliminates the need for such initialization while effectively preventing sagging.

4.2. Complex Dynamics

We also evaluate the performance of our framework in more complex dynamic settings.



Figure 6. Qualitative comparison of the *Curly-wig* experiment. Top is our simulation results. Bottom is the figure from Hsu *et al.* [7].



Figure 7. Hair-hand interaction simulated with our framework using 15k strands (left) and 128 guides with LHS interpolation (right). Unlike interpolation-based methods, our approach handles dense, contact-rich scenarios in real-time without artifacts.

4.2.1. Object Interaction

In order to manage the intensive computations required for complex hair models, in previous works, strand interpolation is often applied to a limited set of guide strands. However, this approach can lead to artifacts, particularly in scenarios involving intricate object interactions. Figure 7 illustrates this effect with hair-hand interaction, where we use 15k fully simulated strands alongside Linear Hair Skinning (LHS) interpolation over 2048 guiding strands. We further investigate hair-solid interaction in Figure 8, using 10,298 fully simulated strands and a neural interpolation model based on CT2Hair [20]. Unlike traditional methods, neural-driven approaches depend heavily on the training dataset



Figure 8. Simulation of hair interacting with a hollow sphere, using 128 guiding strands (left) with interpolation based on the neural approach from [20] (middle), and 10,298 fully simulated strands with AMS (right). The neural method increases the hair count without considering the updated rest pose of the head or the introduction of new geometry in the scene (the sphere), resulting in interpolation artifacts and object penetration. In contrast, our framework accurately models the complex interaction between hair and additional geometry, increasing the fidelity throughout the simulation.

and are constrained by its domain, often resulting in artifacts when handling new objects or unexpected motions. Additionally, these models require significant training effort, limiting flexibility in complex, dynamic environments.

4.2.2. Non-Standard Settings

Since MS lacks a mechanism for maintaining global structure, strands lose their intended shape across different lengths, leading to uniform behavior regardless of strand length. In contrast, the biphasic interaction in AMS enhances simulation fidelity by accounting for these variations. This advantage is especially evident in the simulation of non-standard hairstyles, as shown in Figure 1, middle, where we model an asymmetric style. In MS, the shorter portion of the style behaves like fur, whereas our AMS approach captures the distinct dynamics of each section, as demonstrated in the supplemental material. Another significant application is facial hair simulation. As shown in Figure 9, where we simulate a beard using both MS and AMS, the initial shape of the beard is lost in MS. In contrast, our scheme preserves the overall shape and character of facial hair, while producing vivid dynamics.

4.2.3. Extreme Forces

Figure 10 illustrates the progressive hair shape change when strands are subjected to the intense acceleration of a rollercoaster. Our scheme is able to hold the initial hairstyle before intense motion as well as to capture the after-ride hair scramble since we explicitly parametrize non-Hookean responses on the *integrity* coupling of the biphasic interaction. Moreover, our framework captures the distinct dynamical responses of varied hairstyles, such as short, long, and curly.

4.3. Applications

4.3.1. Digital Grooming

Inspired by Daviet *et al.* [4], we explore the editing and interaction capabilities of our model by enabling diverse



Figure 9. Time evolution (from left to right) of facial hair simulated using MS (top) and AMS (bottom). Our augmented formulation introduces key interactions that preserve the intended structure of facial hair throughout the simulation, while in MS, strands lose their overall form at initialization.

user inputs to transform existing hair assets into new configurations. This is illustrated in Figure 11, where we use an input (left) to compare purely geometrical trimming (center) to our dynamic simulation-based approach (right). Purely geometric approaches lack the flexibility to realistically respond to conditions like wind or complex interactions among hair strands and with external objects.

4.3.2. Facial Tracking Integration

We integrate facial tracking with our framework to enable digital avatars to respond dynamically to user motion, enhancing realism and interactivity. Our approach employs a video-based facial tracking system [5] to extract real-time head motion, which is used to drive the simulated hair. The resulting avatars exhibit temporally coherent and physically plausible behavior, as demonstrated in Figure 12. Please refer to the supplemental video for a real-time demonstration.



Figure 10. Time evolution (from left to right) of hair undergoing *roller-coaster* dynamics simulated with our framework, shown across different styles: long (top), short (middle), and curly (bottom). The non-linear response in the biphasic interaction enables us to capture the progressive loss of global hair features when strands are subjected to intense deformation.

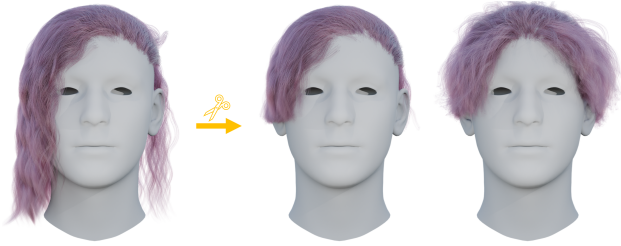


Figure 11. Starting from an initial input (left), we demonstrate purely geometrical trimming (center) versus our dynamic simulation-based trimming (right) where the hair shape changes due to the volume and length change, mimicking real-world effects.

5. Discussion

Our AMS framework enables real-time performance of complex hair dynamics and hair-object interactions with affordable GPU memory consumption, making it feasible to incorporate high-fidelity hair simulations in games and significantly reduce the cost of hair animation in films. To demonstrate this, in the supplementary material, we showcase the real-time simulation of hair and facial hair movements for Wukong [18], a hero character from a recent AAA game, running on a laptop.

Limitations and Future Work. Despite the growing popularity of neural approaches, we demonstrate in this work that data-driven methods are not a cure-all for simulation. By carefully designing physics-based models, we can

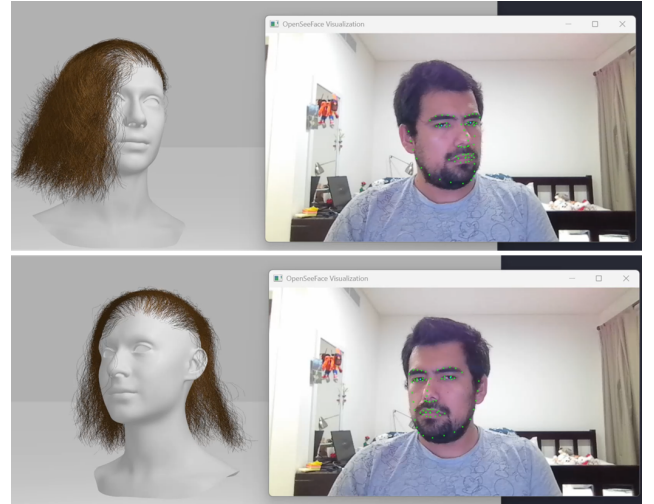


Figure 12. Time evolution (from top to bottom) demonstrating the temporally coherent hair motion of a virtual avatar, driven by video-based facial tracking [5]. The user controls the avatar (left) via video input (right).

achieve both high-efficiency and high-fidelity simulation effects. Future research could explore adapting AMS systems for cloth simulation. As for limitations, our method is an approximation of real-world physics, optimized for speed and visual quality, but it does not guarantee full compliance with real-world physical behavior.

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