

# Refinement of Hair Geometry by Strand Integration

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CyberAgent **AI Lab**

## Digital Human

- Create 3D models of real people by capturing images



Multi-view camera



Video production

## Difficulty of Hair Modeling

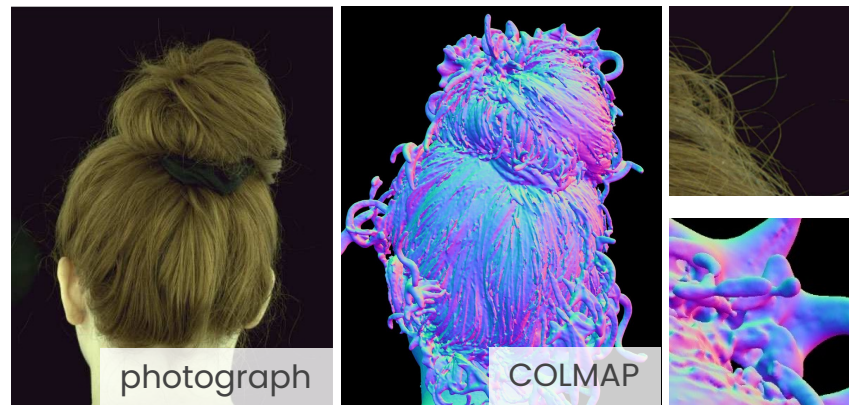
### Hand modeling by CG artists



[Maya XGen Official Doc.]

- Technical expertise and artistic skill
- Laborious and time-consuming task

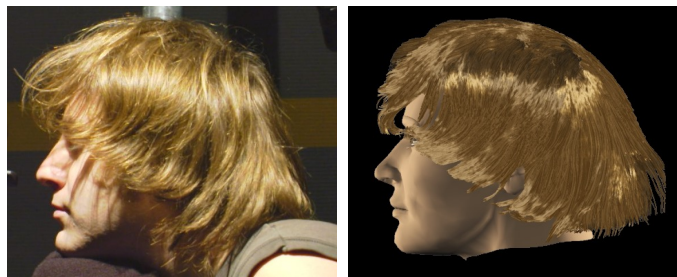
### Using multi-view images



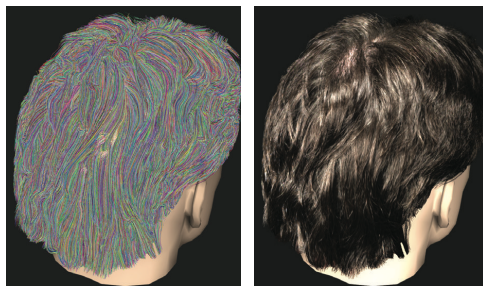
[Nam et al.]

- Conventional MVS does not work

## Related Works : Hair Reconstruction from Multi-view Images



[Paris et al, SIGGRAPH2004]



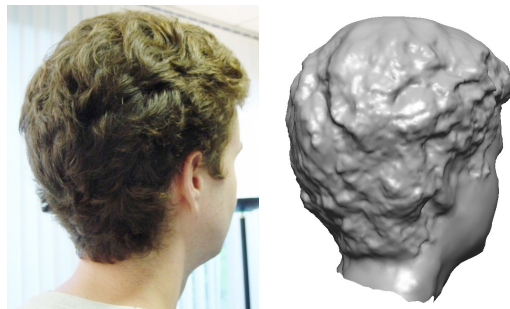
[Paris et al, SIGGRAPH2008]



[Hu et al, SIGGRAPH2014]



[Luo et al, CVPR2012]



[Luo et al, CVPR2013]



[Luo et al, SIGGRAPH2013]

# LPMVS (Line-based PatchMatch Multi-View Stereo) [Nam et al., CVPR2019]

## Strand-accurate Multi-view Hair Capture

Giljoo Nam<sup>\*1</sup> Chenglei Wu<sup>2</sup> Min H. Kim<sup>1</sup> Yaser Sheikh<sup>2</sup>  
<sup>1</sup>KAIST <sup>2</sup>Facebook Reality Labs, Pittsburgh

### Abstract

*Hair is one of the most challenging objects to reconstruct due to its micro-scale structure and a large number of repeated strands with heavy occlusions. In this paper, we present the first method to capture high-fidelity hair geometry with strand-level accuracy. Our method takes three stages to achieve this. In the first stage, a new multi-view stereo method with a slanted support line is proposed to solve the hair correspondences between different views. In detail, we contribute a novel cost function consisting of both photo-consistency term and geometric term that reconstructs each hair pixel as a 3D line. By merging all the depth maps, a point cloud, as well as local line directions for each point, is obtained. Thus, in the second stage, we feature a novel strand reconstruction method with the mean-shift to convert the noisy point data to a set of strands. Lastly, we grow the hair strands with multi-view geometric constraints to elongate the short strands and recover the missing strands, thus significantly increasing the reconstruction completeness. We evaluate our method on both*

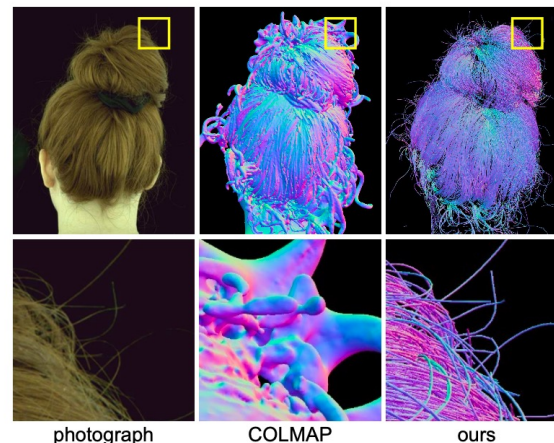


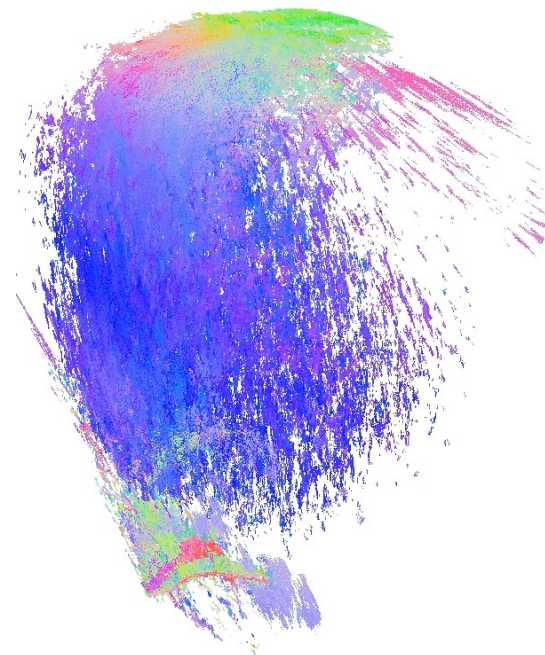
Figure 1. (Left) One of the photographs from multi-view capture. (Middle) Final geometry by traditional MVS (COLMAP [33]). (Right) Final geometry by our method. Our method can produce high-fidelity hair geometry with strand-level accuracy.

# LPMVS (Line-based PatchMatch Multi-View Stereo) [Nam et al., CVPR2019]



Input: Multi-view images

**LPMVS**  
[Nam+, CVPR2019]



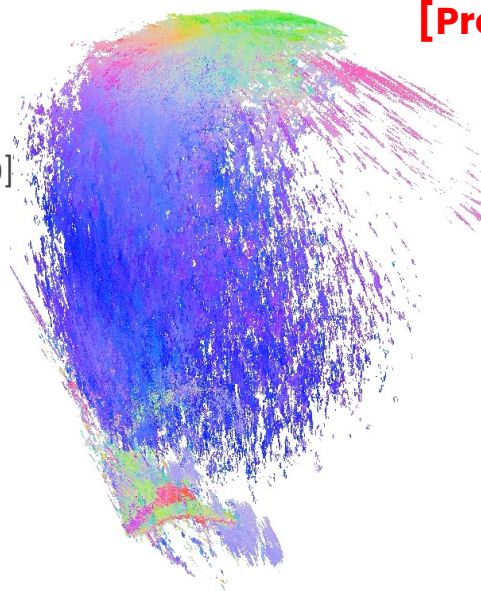
Output: 3D lines (*unfiltered*)

## Our Contribution: Strand Integration



Input: Multi-view images

LPMVS  
[Nam+, CVPR2019]



**[Proposed method]**

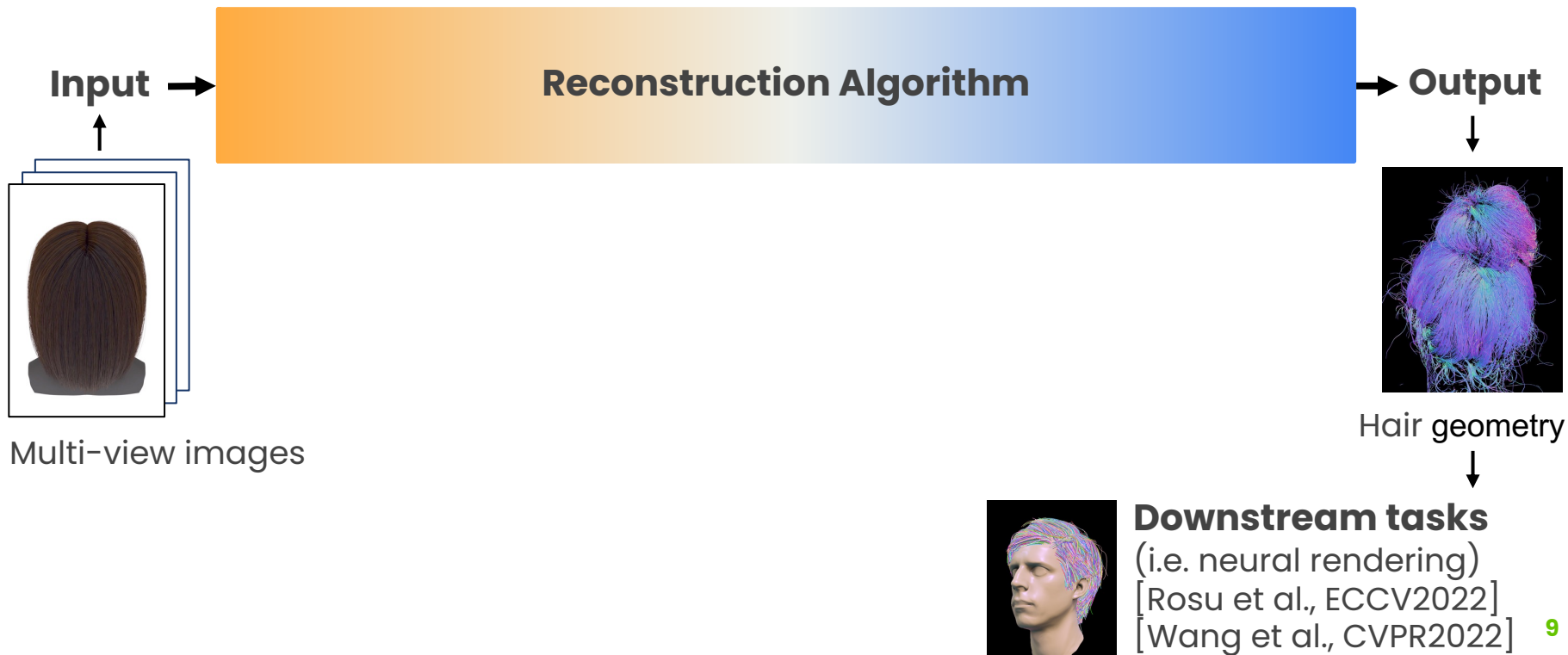
Strand  
Integration



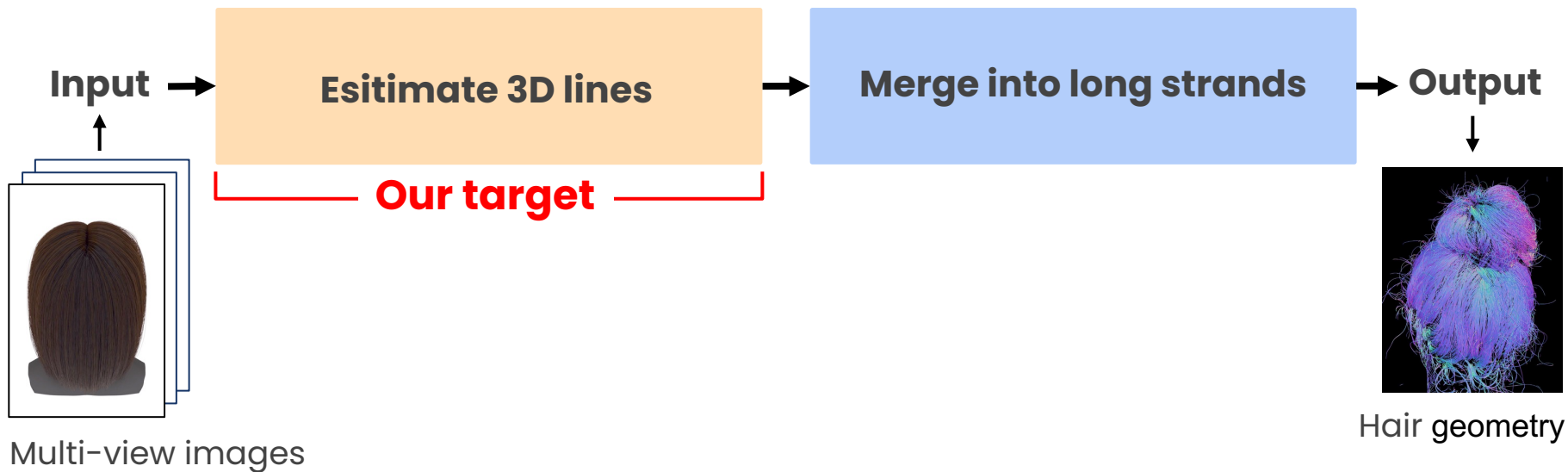
# General Pipeline for Reconstruction of Hair Geometry



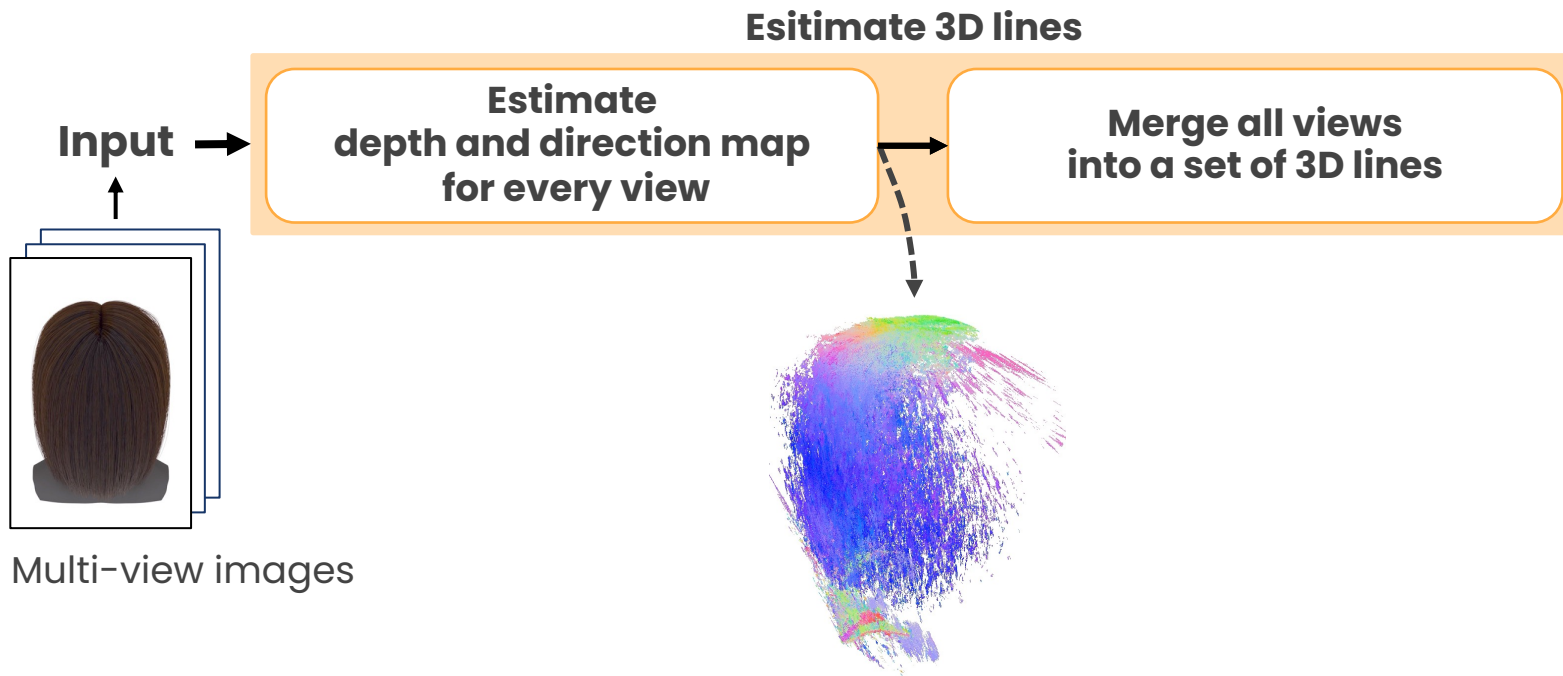
## Reconstruction of Hair Geometry from Multi-view Images



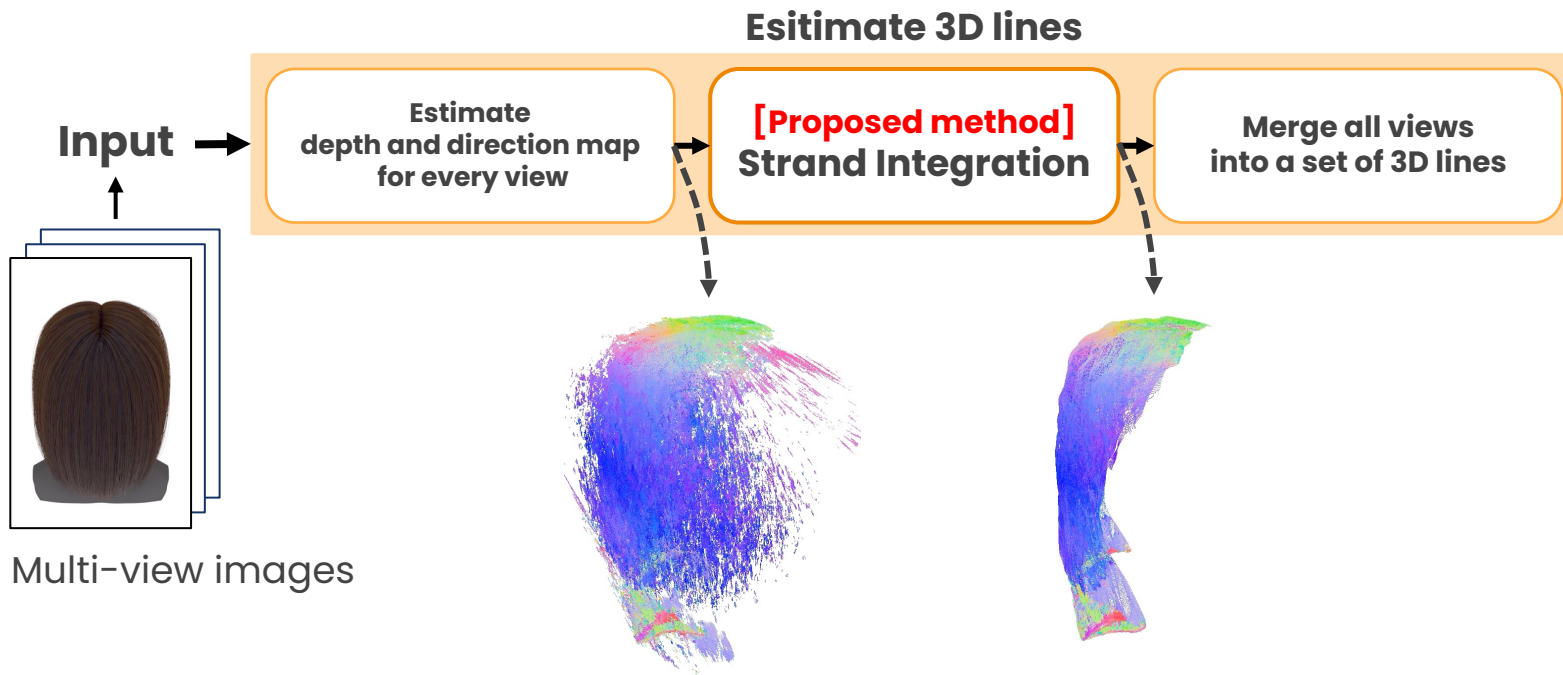
## Reconstruction of Hair Geometry from Multi-view Images



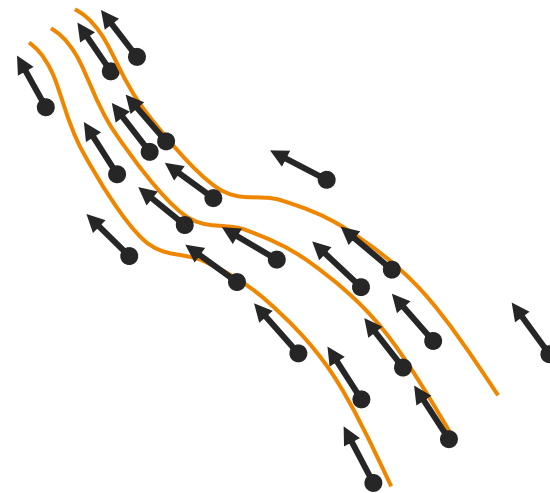
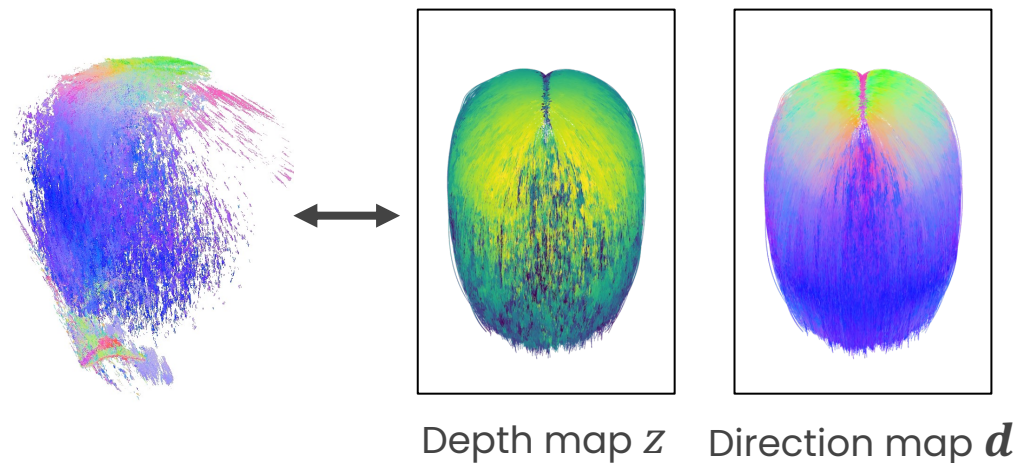
## Reconstruction of Hair Geometry from Multi-view Images



# Reconstruction of Hair Geometry from Multi-view Images

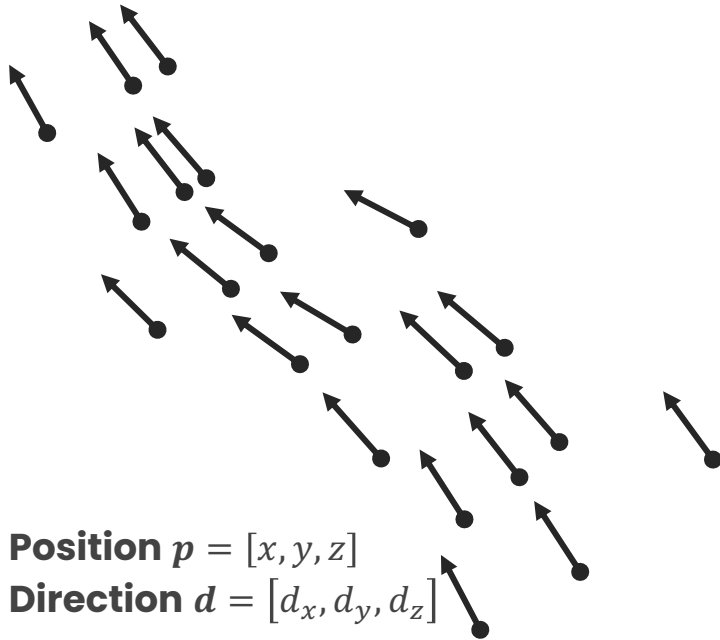


## Representation of Hair Geometry by 3D Lines



- **Position**  $p = [x, y, z]$
- **Direction**  $d = [d_x, d_y, d_z]$

## Problem of the Existing Method (LPMVS [Nam et al.]



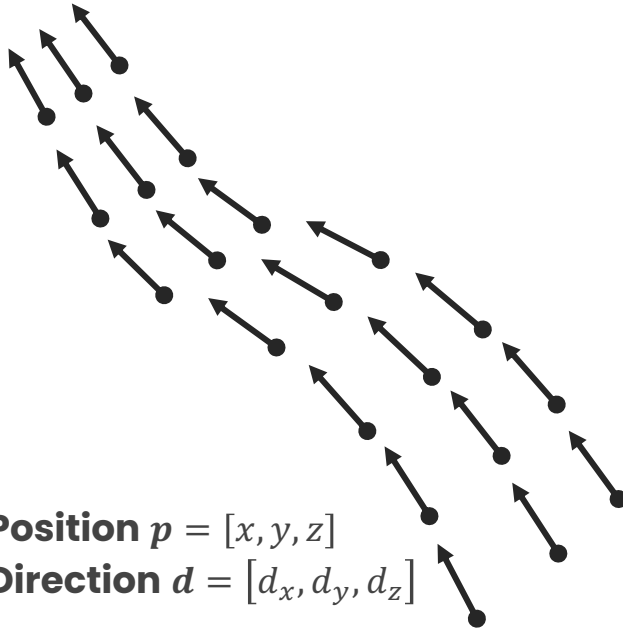
- **Position**  $p = [x, y, z]$
- **Direction**  $d = [d_x, d_y, d_z]$

Hair strands are smoothly connected...

### **Problem**

Does NOT consider  
the spatial coherence of 3D lines.

## Our Method: Strand Integration



- **Position**  $p = [x, y, z]$
- **Direction**  $d = [d_x, d_y, d_z]$

Hair strands are smoothly connected...

### Problem

Does NOT consider the spatial coherence of 3D lines.

### Our Method: Strand Integration

Refine the position of hair strands by using the direction.

# Strand Integration



## Loss Function

Find the **depth map**  $z$  which minimizes

$$\mathcal{L}(z) = \lambda_d \mathcal{L}_d(z) + \mathcal{L}_z(z)$$

Direction loss      Depth loss

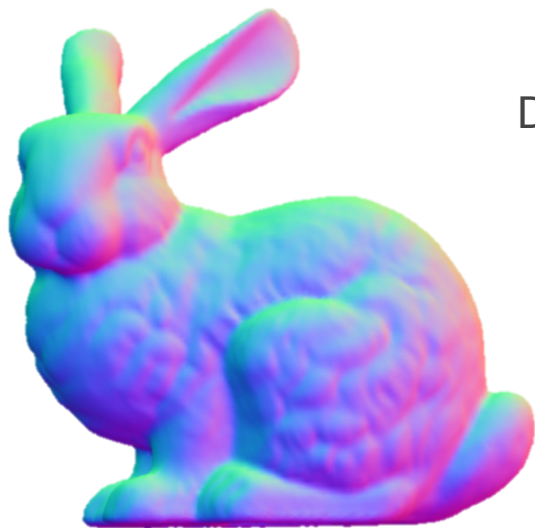


## Direction Loss: $\mathcal{L}_d$

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- Harness the **position** and **direction** information for improving geometrical coherence.
- Inspired by **Normal Integration**.

## Normal Integration: Depth from Normal

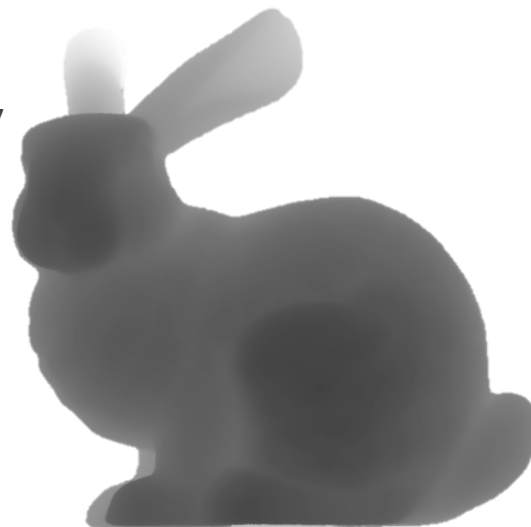


Normal map  $n$

Differentiation  $\nabla$



Integration  $\int$



Depth map  $z$

## Strand Integration: Depth from Direction

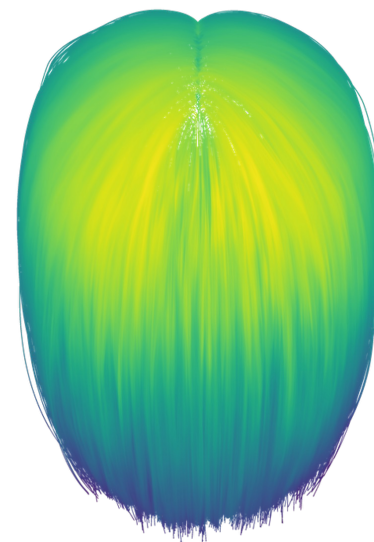


Direction map  $d$

Differentiation  $\nabla$

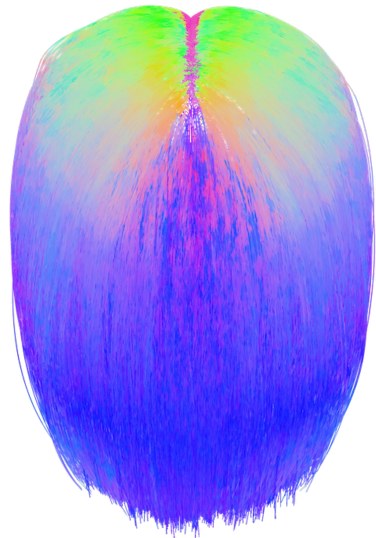


Integration  $\int$



Depth map  $z$

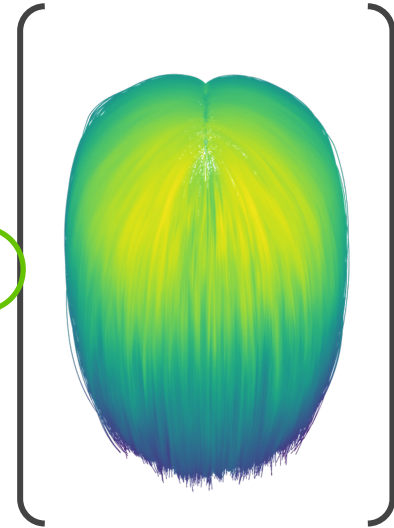
## Strand Integration: Depth from Direction



Direction map  $d$

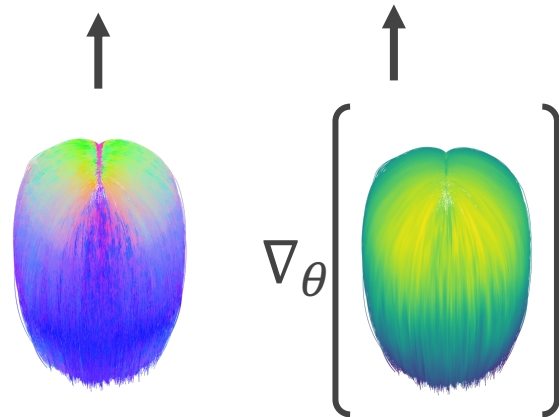
$$= \nabla_{\theta}$$


**Orientation**  
*of the strand*



Differentiation of depth map  $\nabla_{\theta} z$

## Direction Loss: $\mathcal{L}_d$

$$\mathcal{L}_d(\mathbf{z}) = \sum (d_{\text{prior}} - \nabla_{\theta}(\mathbf{z}))^2$$


The diagram illustrates the Direction Loss formula. It shows two heatmaps of a bird-like shape. The left heatmap is labeled  $d_{\text{prior}}$  and the right heatmap is labeled  $\nabla_{\theta}(\mathbf{z})$ . Arrows point from each heatmap to its corresponding term in the formula.

## Loss Function

Find the **depth map**  $z$  which minimizes

$$\mathcal{L}(z) = \lambda_d \mathcal{L}_d(z) + \mathcal{L}_z(z)$$

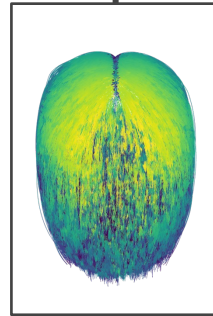
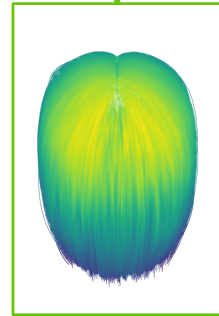
Direction loss      Depth loss



## Depth Loss : $\mathcal{L}_z$

- Use prior depth map as anchor points.
- Incorporate the multi-view constraint into the refinement process.

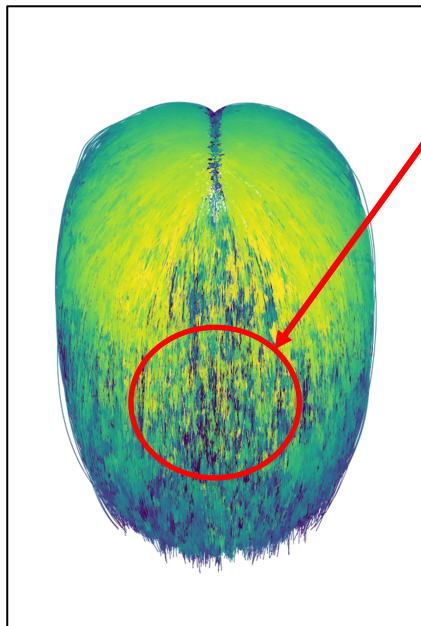
$$\mathcal{L}_z(\mathbf{z}) = \sum (\mathbf{z} - z_{\text{prior}})^2$$



Contain inaccurate  
depth values

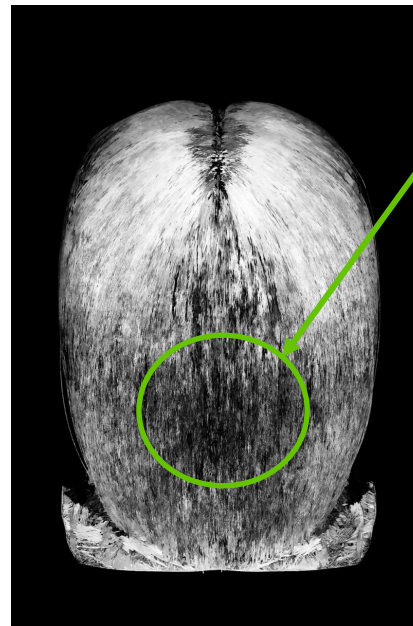


## 3D Line Consistency Map



Prior depth map

**Inaccurate depth**  
distort  
the refinement result

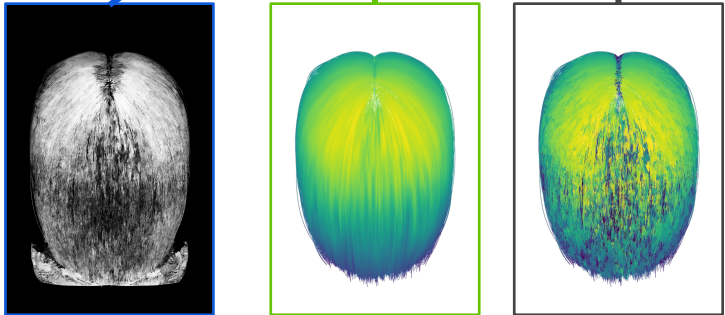


Consistency Map  
with respect to  
neighboring views

**Low consistency**  
use as per-pixel weight  
to ignore  
the inaccurate depth

## Depth Loss (w/ Consistency Map) : $\mathcal{L}_z$

- Use prior depth map as anchor points.
- Incorporate the multi-view constraint into the refinement process.

$$\mathcal{L}_z(\mathbf{z}) = \sum c(\mathbf{z} - \mathbf{z}_{\text{prior}})^2$$


## Loss Function

---

Find the **depth map**  $z$  which minimizes

$$\mathcal{L}(z) = \lambda_d \mathcal{L}_d(z) + \mathcal{L}_z(z)$$

Direction loss      Depth loss

## Loss Function with Normal Loss

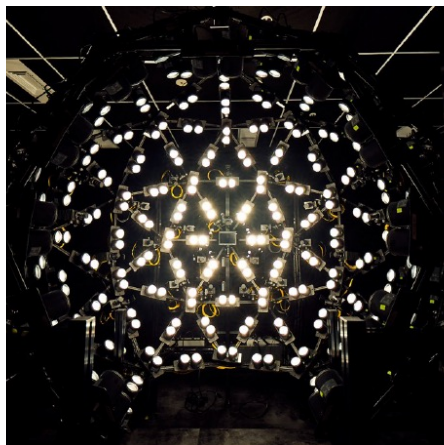
Find the **depth map**  $z$  which minimizes

$$\mathcal{L}(z) = \lambda_n \mathcal{L}_n(z) + \lambda_d \mathcal{L}_d(z) + \mathcal{L}_z(z)$$

Normal loss  
(optional)Direction lossDepth loss

## Normal Loss (optional): $\mathcal{L}_n$

- If we obtain the normal map, we can use it as **optional loss**.
- Normal should be perpendicular to the strand direction.



Light stage system



Photometric images



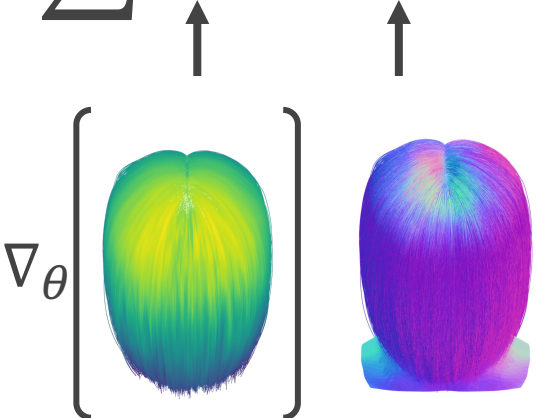
Photometric  
stereo



Normal map

## Normal Loss (optional): $\mathcal{L}_n$

- If we obtain the normal map, we can use it as **optional loss**.
- Normal should be perpendicular to the strand direction.

$$\mathcal{L}_n(\mathbf{z}) = \sum (\mathbf{d} \cdot \mathbf{n}_{\text{prior}})^2$$


The diagram illustrates the Normal Loss calculation. The equation shows the dot product of the strand direction vector  $\mathbf{d}$  and the normal vector  $\mathbf{n}_{\text{prior}}$ , squared, summed over all strands. Below the equation, two hair models are shown. The left model is enclosed in large square brackets and labeled with the gradient operator  $\nabla_{\theta}$ . The right model is a standard hair model. Arrows point from the labels  $\mathbf{d}$  and  $\mathbf{n}_{\text{prior}}$  in the equation to the corresponding models.

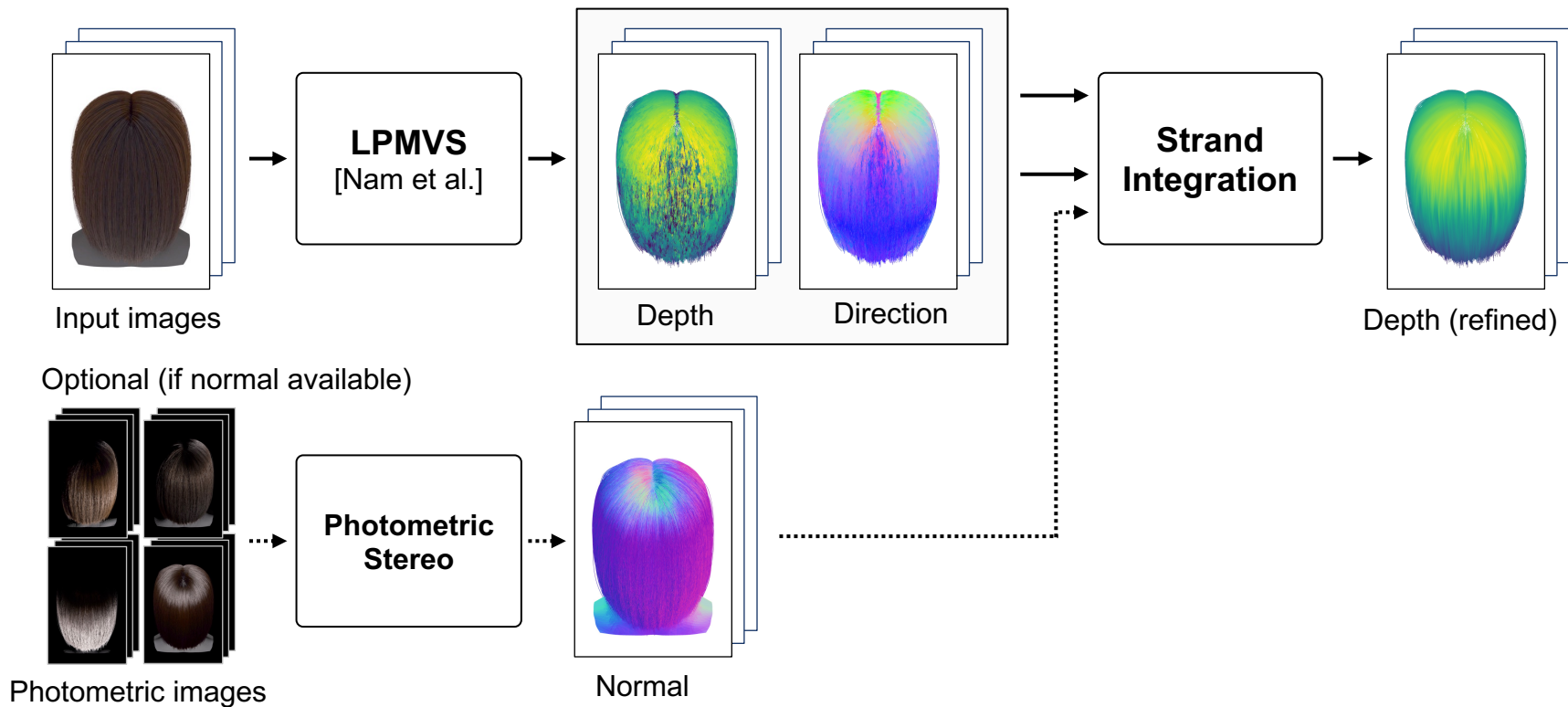
## Loss Function with Normal Loss

Find the **depth map**  $z$  which minimizes

$$\mathcal{L}(z) = \lambda_n \mathcal{L}_n(z) + \lambda_d \mathcal{L}_d(z) + \mathcal{L}_z(z)$$

Normal loss  
(optional)Direction lossDepth loss

## Overall Pipeline of Strand Integration





# Experiment

## Implementation

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- LPMVS [Nam et al.]
  - The official implementation is not publicly available.
  - CPU-based reimplementaion in C++.
- Strand Integration
  - Use PyTorch as a general gradient descent solver.
  - 20 min for each view on Apple M1 Max. 11 MP(2730x4096) image.

## Synthetic Data

- Rendered with pbrt-v4
- 60 views
- 2730x4096
- 4 hairstyles



Straight



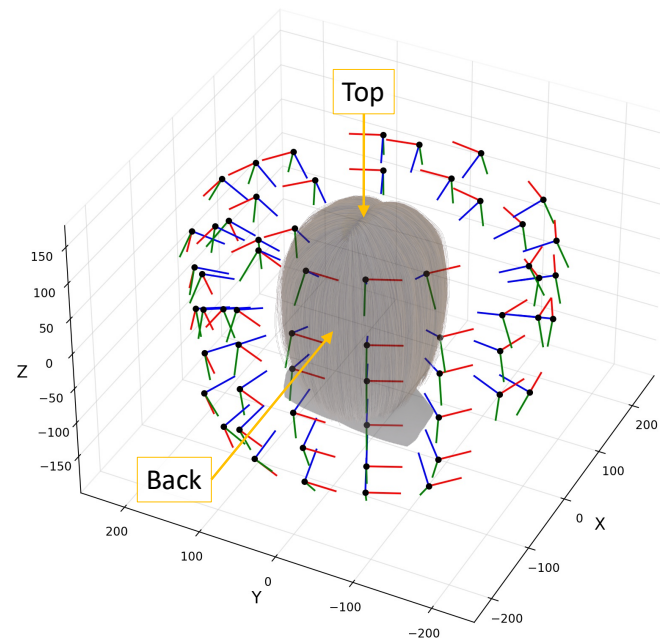
Curly



Wavy



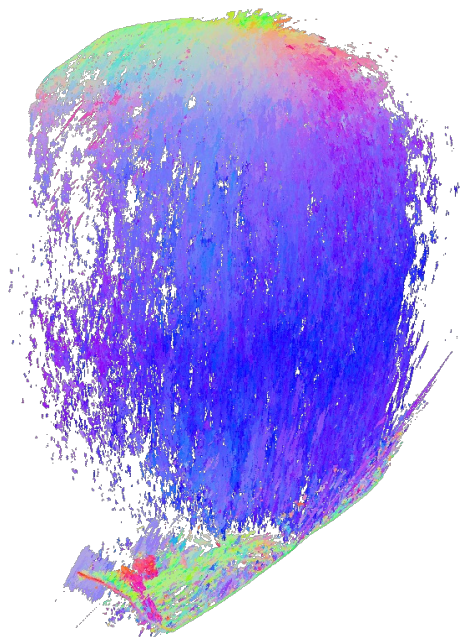
Wavythin



## Result: Straight Hair



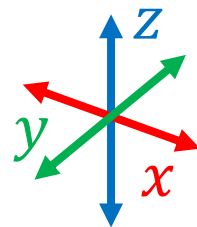
**Ground Truth**



**LPMVS**  
[Nam et al.]



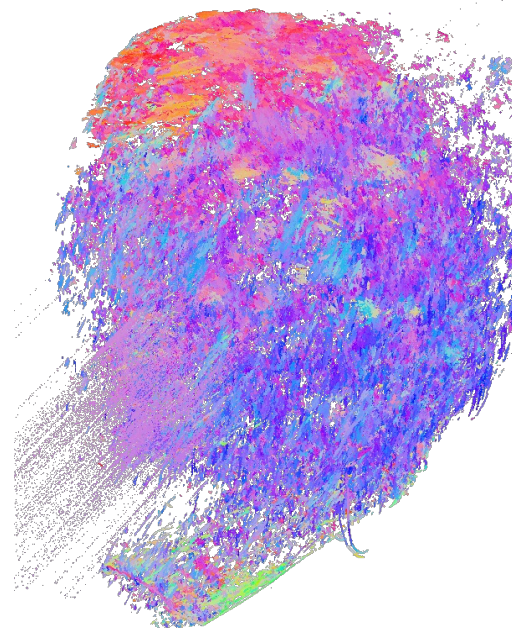
**Strand Integration**  
(ours)



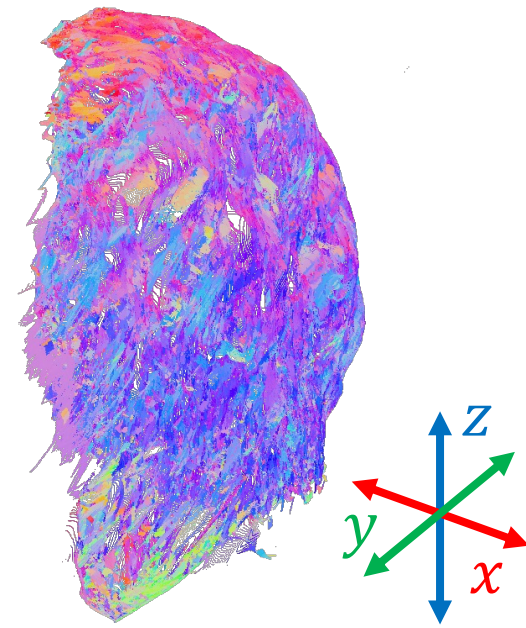
## Result: Curly Hair



**Ground Truth**



**LPMVS**  
[Nam et al.]

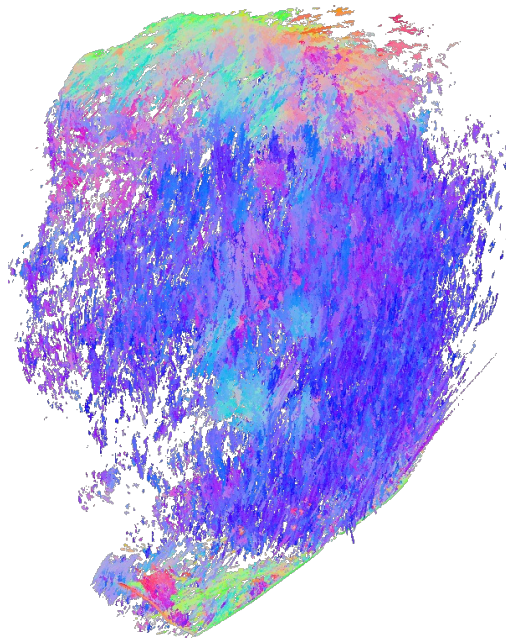


**Strand Integration**  
(ours)

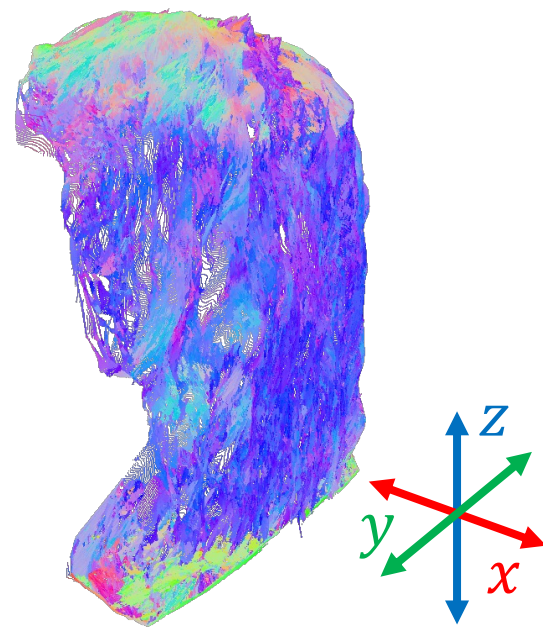
## Result: Wavy Hair



**Ground Truth**



**LPMVS**  
[Nam et al.]

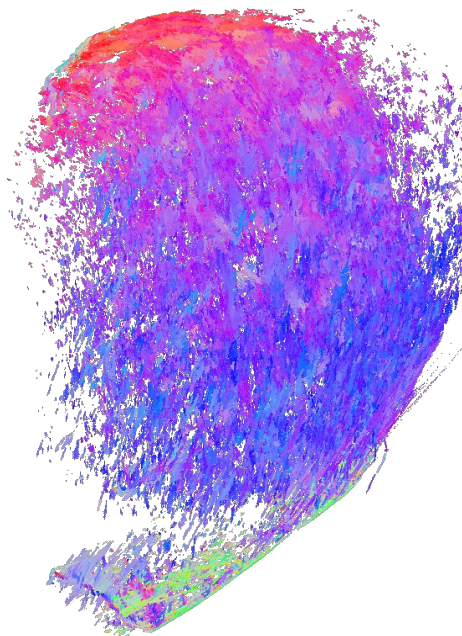


**Strand Integration**  
(ours)

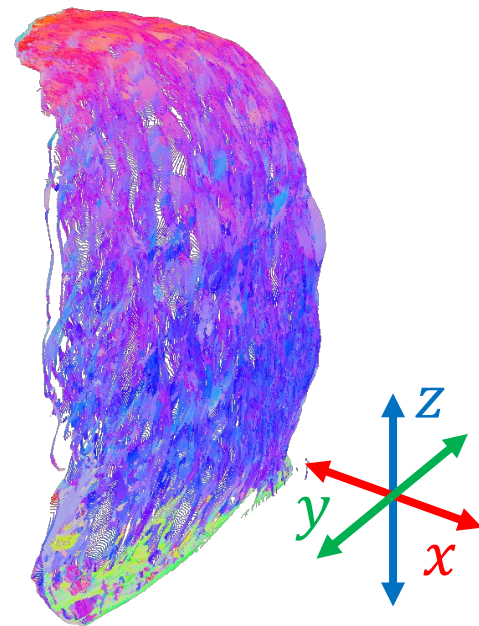
## Result: Wavythin Hair



**Ground Truth**

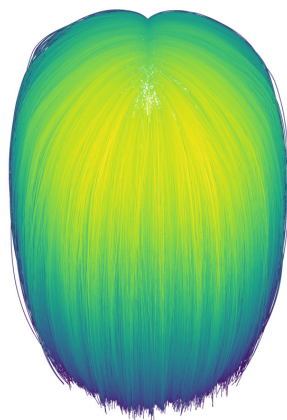


**LPMVS**  
[Nam et al.]

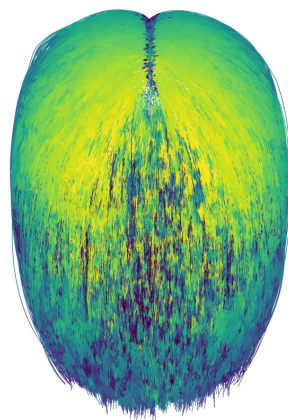


**Strand Integration**  
(ours)

## Error Analysis on Depth Map

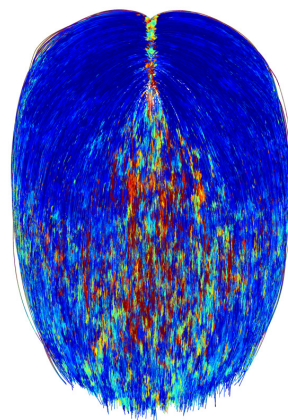


Ground Truth

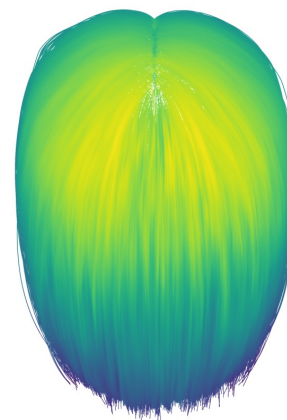


LPMVS [Nam et al.]

MAE : 30.05  
RMSE: 52.57



Abs. error



Strand Integration

MAE : **9.67**  
RMSE: **14.92**



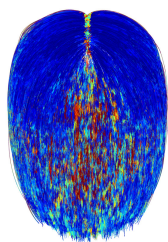
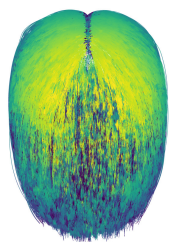
Abs. error



## Error Analysis on Depth Map

MAE / RMSE

### Straight



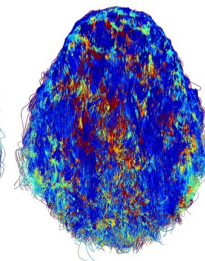
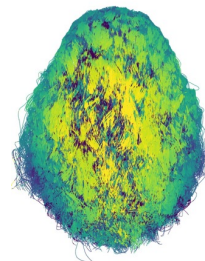
LPMVS

30.05 / 52.57

Strand Integration

**9.76 / 15.03**

### Curly



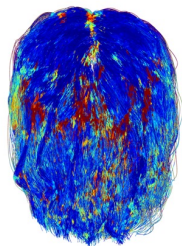
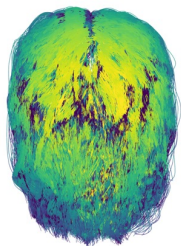
LPMVS

41.47 / 67.87

Strand Integration

**18.10 / 27.07**

### Wavy



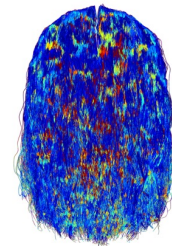
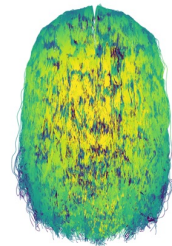
LPMVS

34.21 / 60.30

Strand Integration

**12.20 / 20.57**

### Wavythin



LPMVS

34.96 / 58.54

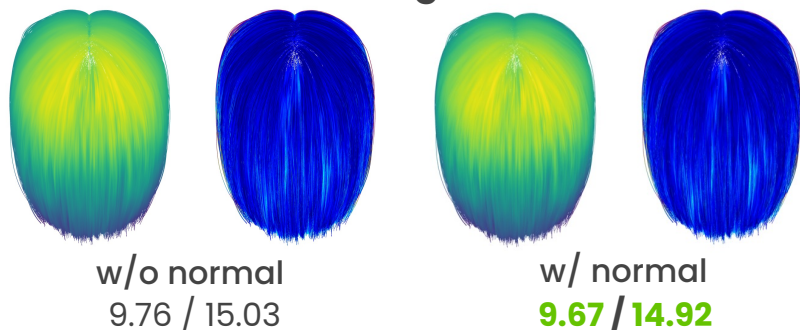
Strand Integration

**11.34 / 19.36**

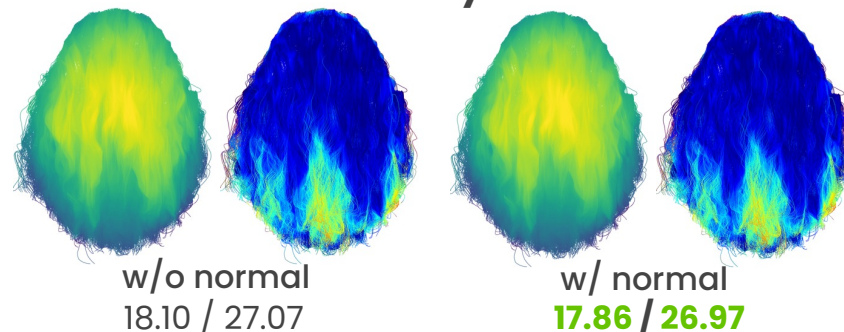
## Ablation Study of Normal Loss

MAE / RMSE

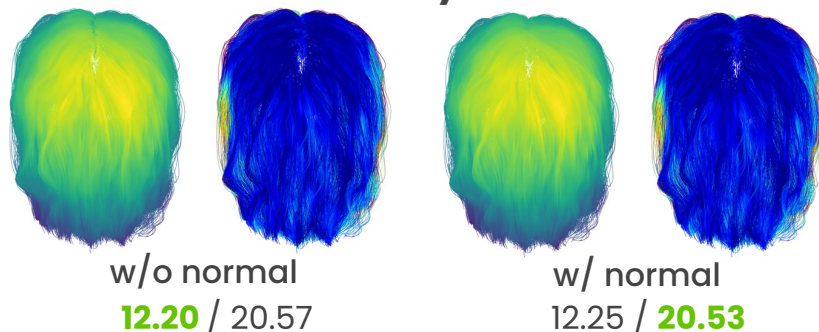
### Straight



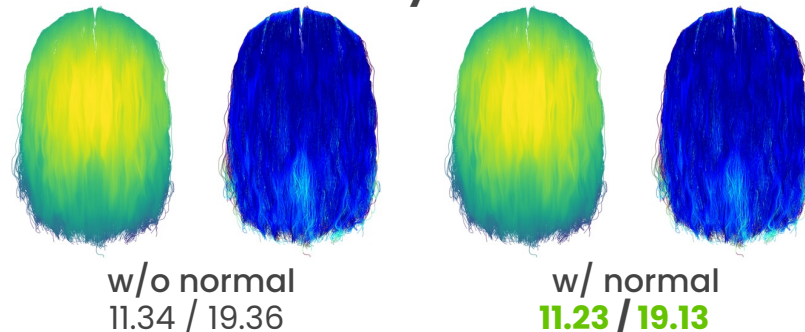
### Curly



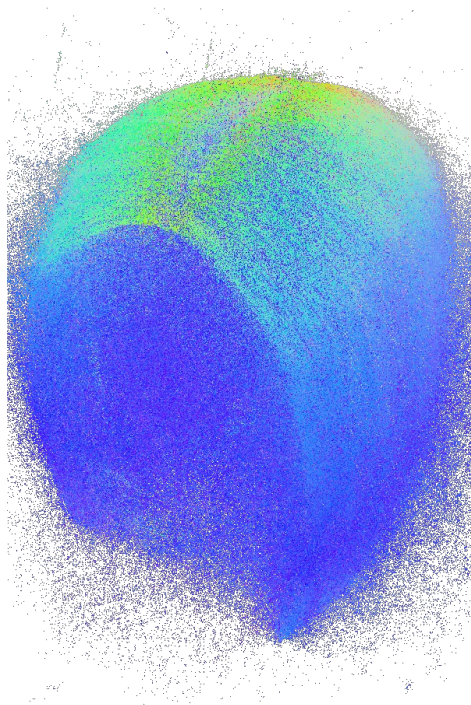
### Wavy



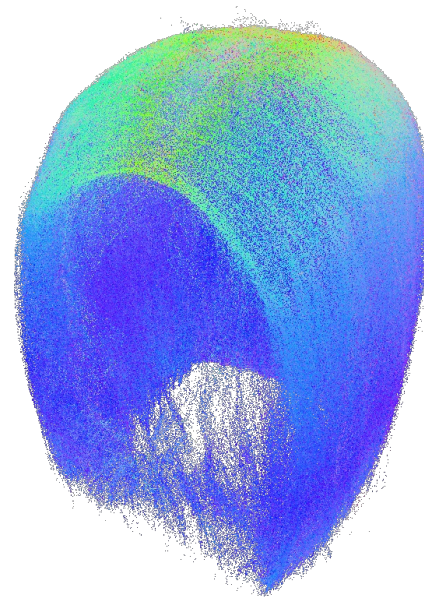
### Wavythin



## Result: Merged Point Cloud



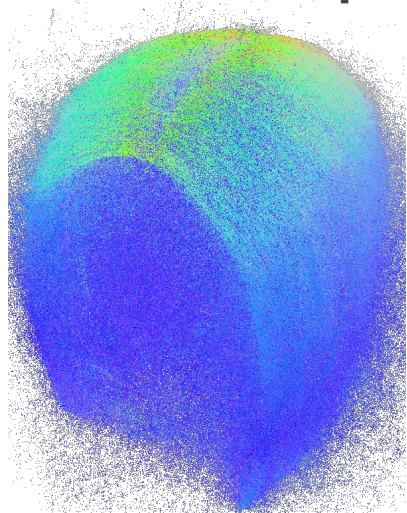
LPMVS [Nam+]



Strand Integration

## Result: Merged Point Cloud

All point cloud

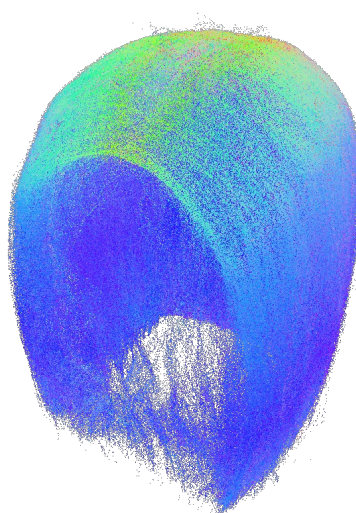


Number  
of points

$297 \times 10^6$

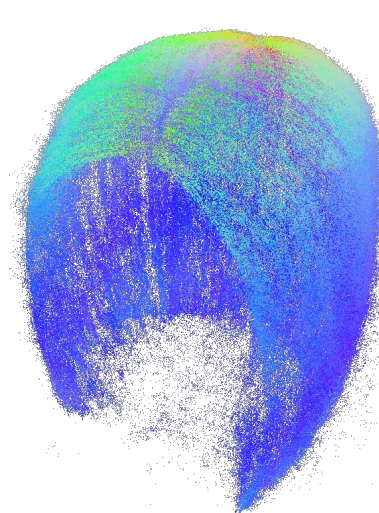
LPMVS [Nam+]

After filtered



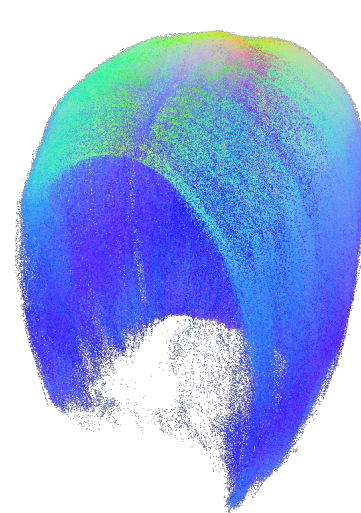
$297 \times 10^6$

Strand Integration



$85 \times 10^6$

LPMVS [Nam+]



$175 \times 10^6$

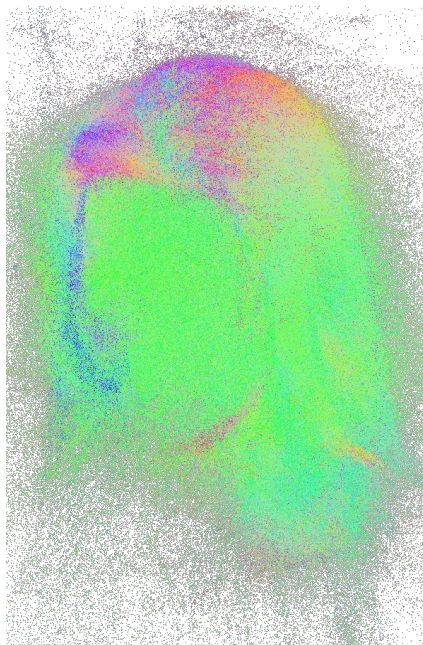
Strand Integration

## Real Data

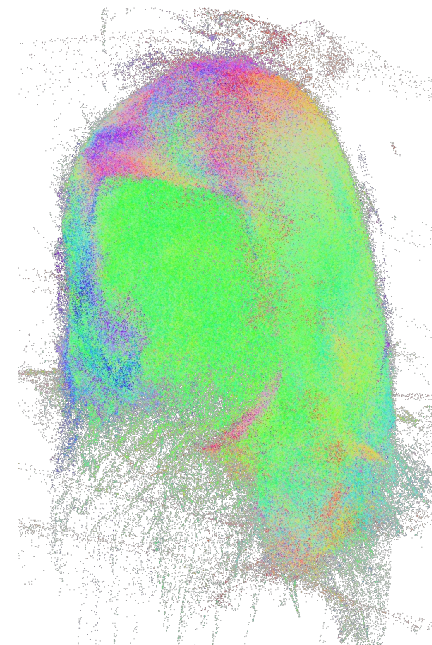
- 60 views
- 5315x8001
- Long hair



## Result: Real Data



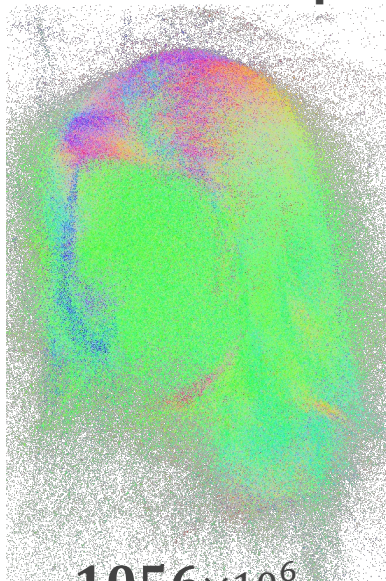
**LPMVS [Nam+]**



**Strand Integration**

## Result: Real Data

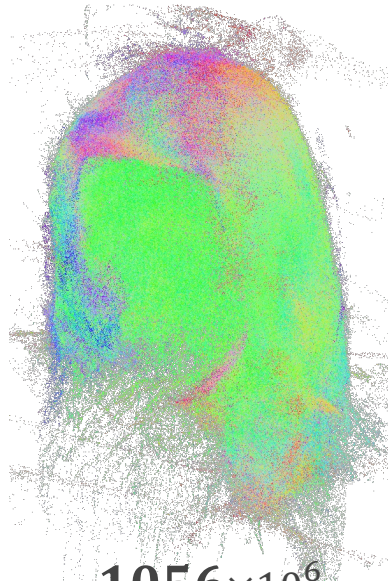
### All point cloud



Number  
of points

$1056 \times 10^6$

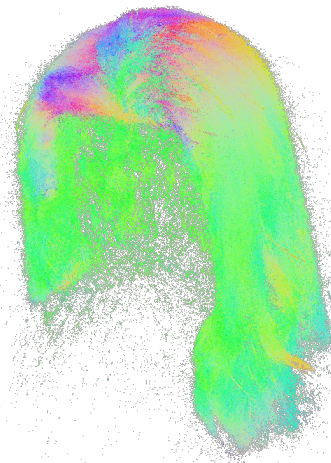
LPMVS [Nam+]



$1056 \times 10^6$

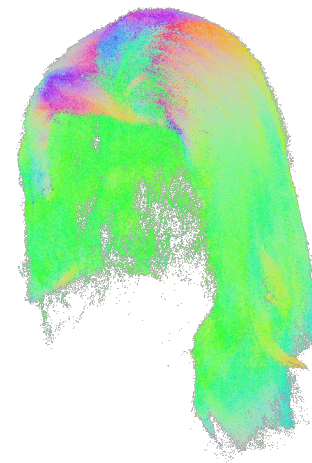
Strand Integration

### After filtering



$214 \times 10^6$

LPMVS [Nam+]



$300 \times 10^6$

Strand Integration

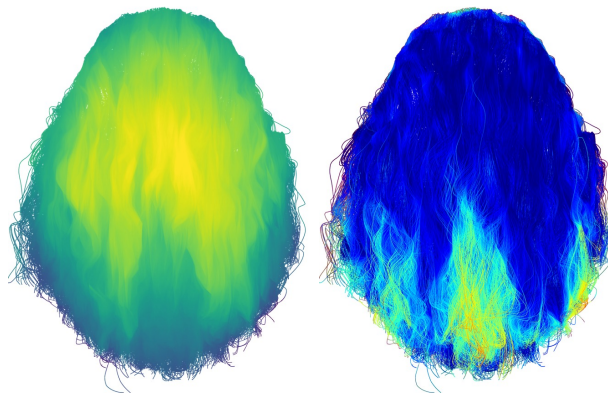
## Limitation

- Assume that hair is continuous and coherent everywhere.
- Break when the hair is strongly curled or scattered.



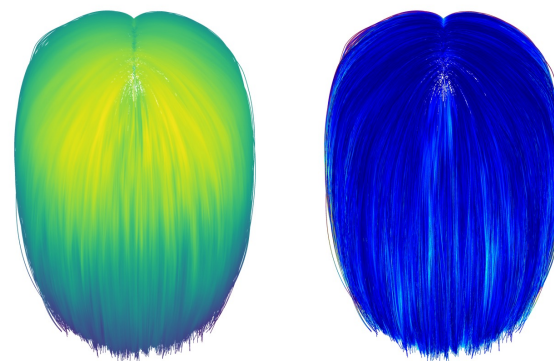
MAE / RMSE

Curly



18.10 / 27.07

Straight



9.76 / 15.03



## Official Code on GitHub

Official implementation  
**Strand Integration**

Unofficial implementation  
**LPMVS**  
[Nam et al., CVPR2019]

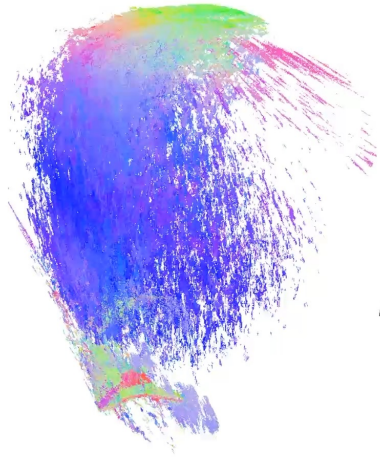
**Synthetic data of  
multi-view images**



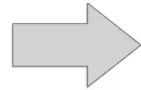
Project page

## Conclusion

- **Strand Integration:** Refine the inaccurate hair strand by integrating the gradient along the hair strand.



LPMVS [Nam+, CVPR'19]



*Refinement*



Strand Integration (ours)



Project page