ROME: REALISTIC ONE-SHOT MESH-BASED HEAD AVATARS

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ECCV Under-Review

(Released to Arxiv 17/June)

Samsung AI Moscow

DAVIAN

Data and Visual Analytics Lab

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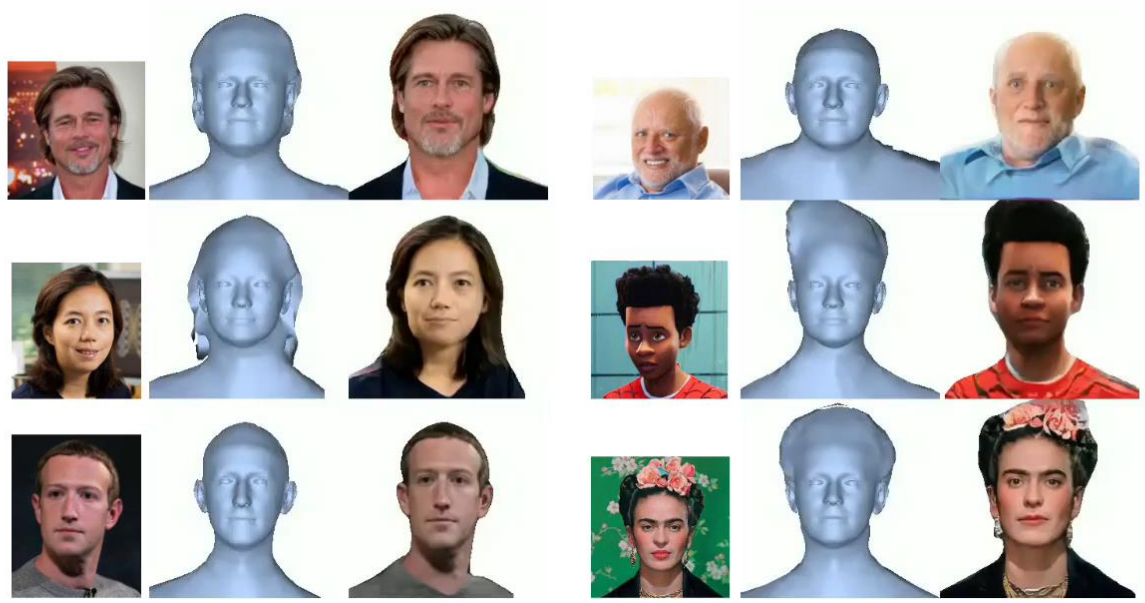

Preliminaries – Taxonomy

Head Reenactment
(a.k.a. Neural Talking Head)

- 2D-oper.
  - w/ 3DMM
  - KP-based
  - No Geometry (latent-based)
- 3D-oper.
  - KP-based
  - Mesh-based

Tencent AI Lab

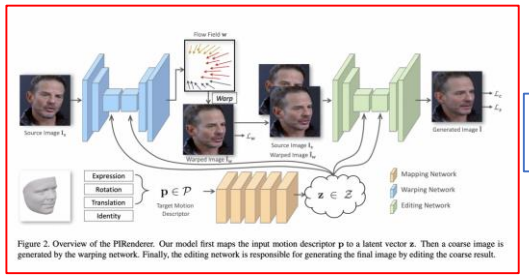

Figure 2. Overview of the PIRenderer. Our model first maps the input motion descriptor p to a latent vector z. Then a coarse image is generated by the warping network. Finally, the editing network is responsible for generating the final image by editing the coarse result.

PIRenderer(ICCV 2021)

Few-shot TH(ICCV 2019)

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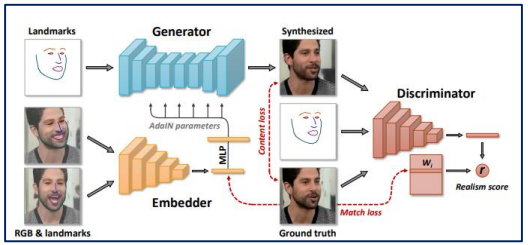
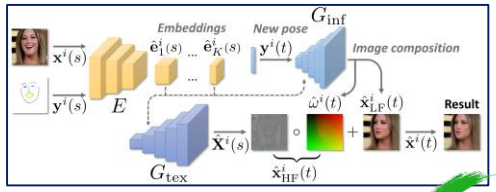
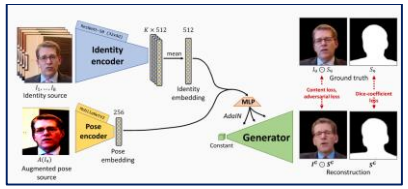


Fast-bi(ECCV 2020)

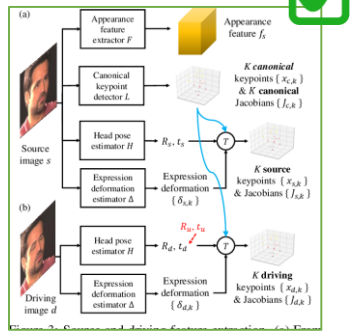


Samsung Research



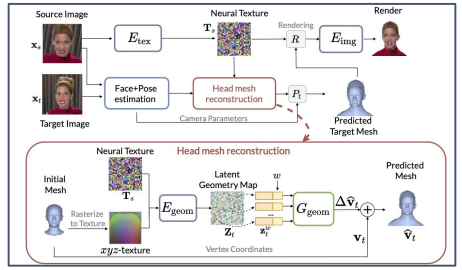
LPD(CVPR 2020)

NVIDIA



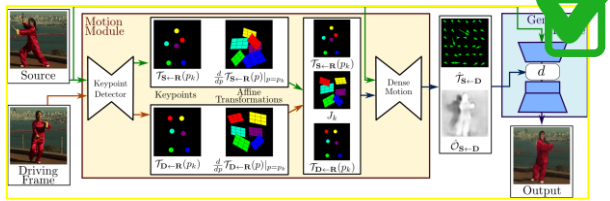
OSFV(CVPR 2021)

Samsung Research



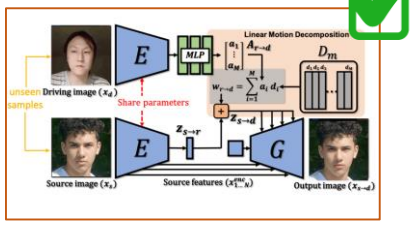
ROME(ECCV 2022(?))

Snap Inc.



FOMM(NIPS 2019)

Inria



LIA(ICLR 2022)

OVERVIEW(CONT'D) - STRENGTHS

- Strengths from two Perspectives
  - Head recon. : Viable to handle non-facial parts(e.g., hear and torso)

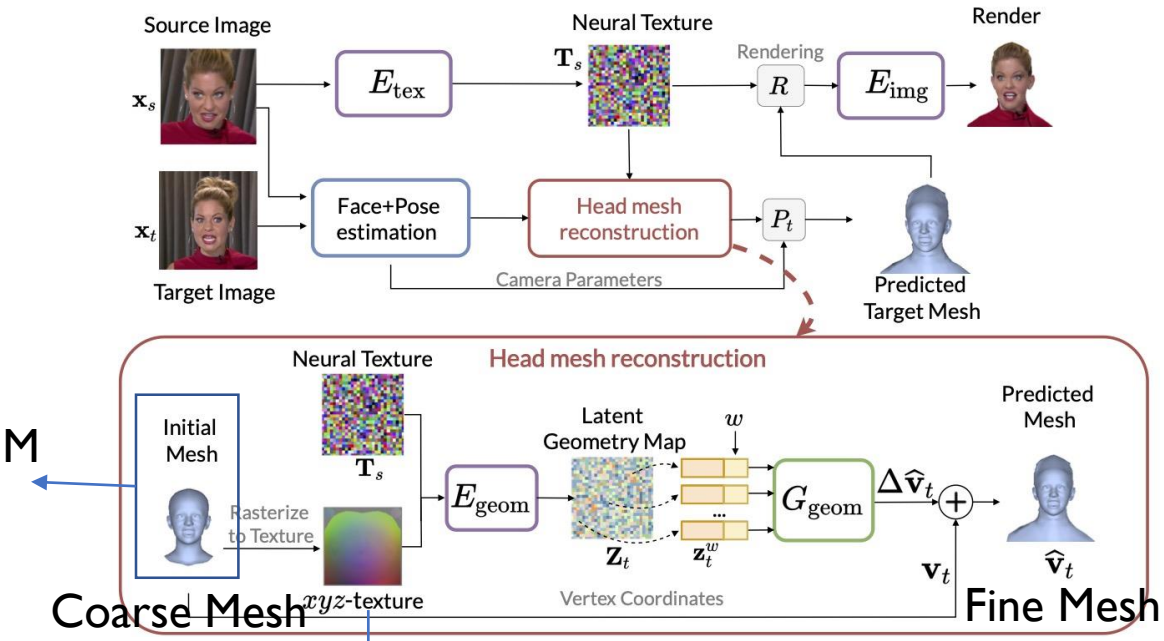
* From DECA(SIGGRAPH 2021)

  - Talking head : Viable to handle unseen facial parts or large drv/src-discrepancy (e.g., one-side facing smthng)

** From DAGAN(CVPR 2022)

Overview – Pipeline(cont'd)

1. Rule-based data process



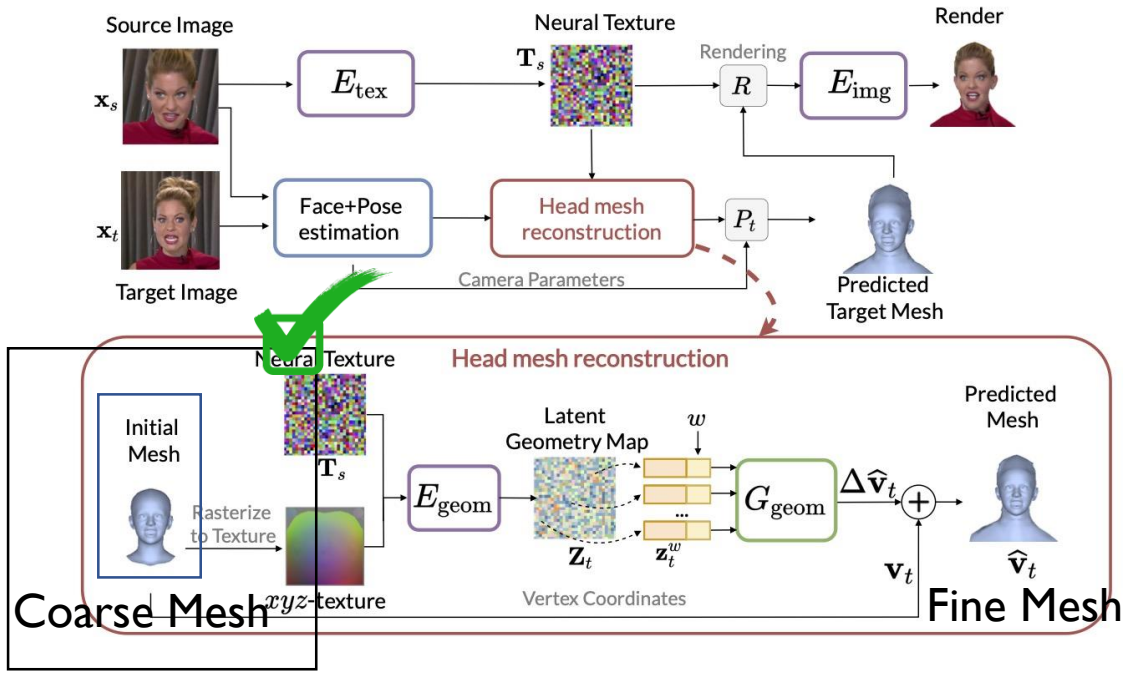
From off-the-shelf 3DMM extractor(DECA)

* 3DMM: representing human head from 3D scanned mesh PCA-based parameterized(Shape and Expression)

Implies which 2d coordinate corresponds to vertex

Overview – Pipeline(cont'd)

2. How 3DMM works? How to reconstruct the Initial Mesh?

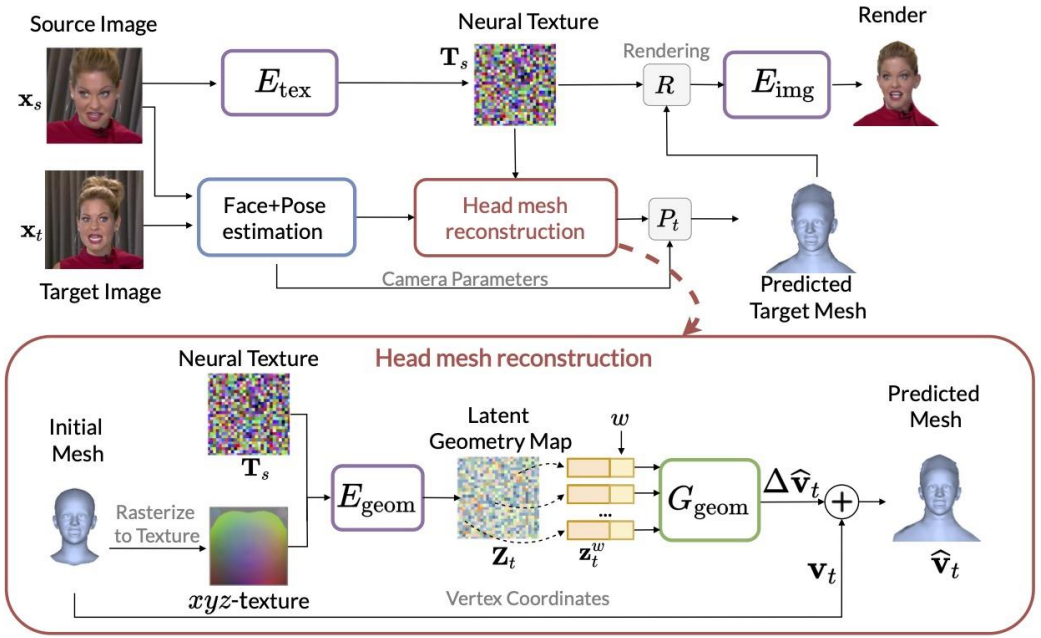


$$\boldsymbol{v}(\phi, \psi, \theta) = \mathrm{W}(\boldsymbol{v}_{base} + \beta\phi + D\psi, \theta)$$

Where,
ϕ: Shape parameter
ψ: Expression parameter
θ: Head pose parameter

*Src: Shape
*Tgt: Expression and Cam/Head pose

Overview – Loss functions



Novel losses

$$\mathcal{L}_{\text{occ}} = \lambda_{\text{hair}} \left\| \hat{\mathbf{o}}_t^{\text{hair}} - \mathbf{s}_t^{\text{hair}} \right\|_2^2 + \lambda_{\text{o}} \left\| \hat{\mathbf{o}}_t - \mathbf{s}_t \right\|_2^2.$$

$$\mathcal{L}_{\text{chm}} = \frac{1}{2N_t} \sum_{\hat{p}_t \in \hat{\mathbf{p}}_t} \left\| \hat{p}_t - \arg\min_{p \in \mathbf{p}_t} \left\| p - \hat{p}_t \right\| \right\| + \frac{1}{2N_t} \sum_{p_t \in \mathbf{p}_t} \left\| p_t - \arg\min_{\hat{p} \in \hat{\mathbf{p}}_t} \left\| \hat{p} - p_t \right\| \right\|.$$

$$\mathcal{L}_{\text{lap}} = \frac{1}{V} \sum_{i=1}^{V} \left\| \Delta \hat{\mathbf{v}}_i - \frac{1}{\mathcal{N}(i)} \sum_{j \in \mathcal{N}(i)} \Delta \hat{\mathbf{v}}_j \right\|_1,$$

Where,
p_t : sampled set of 2D points in the predicted segmentation mask s_t
$\hat{p_t}$: projected 2D vertices coordinate at the target image

align

regularization

Widely-used losses

$$L_{adv} + L_{perc} + L_{arcface} + L_{dice}$$

Results(cont'd)

Comparison with Head Reenactment models

	self-reenactment			cross-reenactment		
Method	LPIPS↓	SSIM↑	PSNR↑	FID↓	CSIM↑	IQA↑
FOMM	0.09	0.87	25.8	52.95	0.53	55.9
Bi-Layer	0.08	0.83	23.7	51.4	0.56	50.48
TPSMM	0.09	0.85	26.1	49.27	0.57	59.5
ROME	0.08	0.86	26.2	45.32	0.62	66.3

Ablation Studies

Result

Limitations

- Mesh resolution

(b) Limitations