



## MIGS: Multi-Identity Gaussian Splatting via Tensor Decomposition

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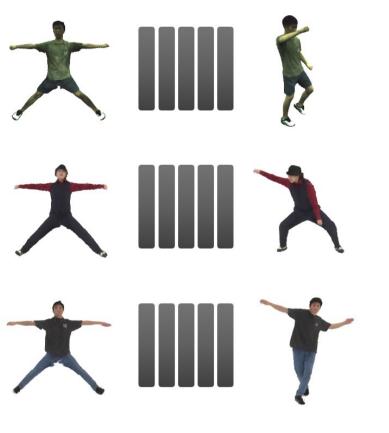




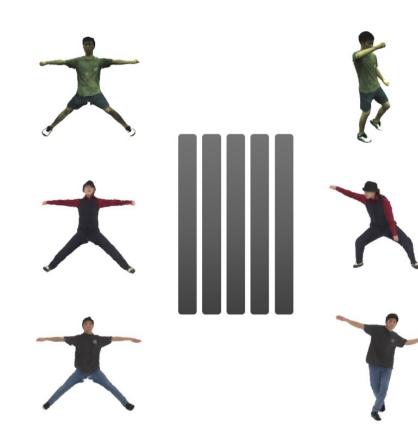
## **Motivation**



- ✓ Unified multi-identity neural representation of human avatars
- ✓ Robust animation under novel poses, out of the training distribution
- ✓ Significant decrease in the total number of learnable parameters



Single-Identity Models (Standard)

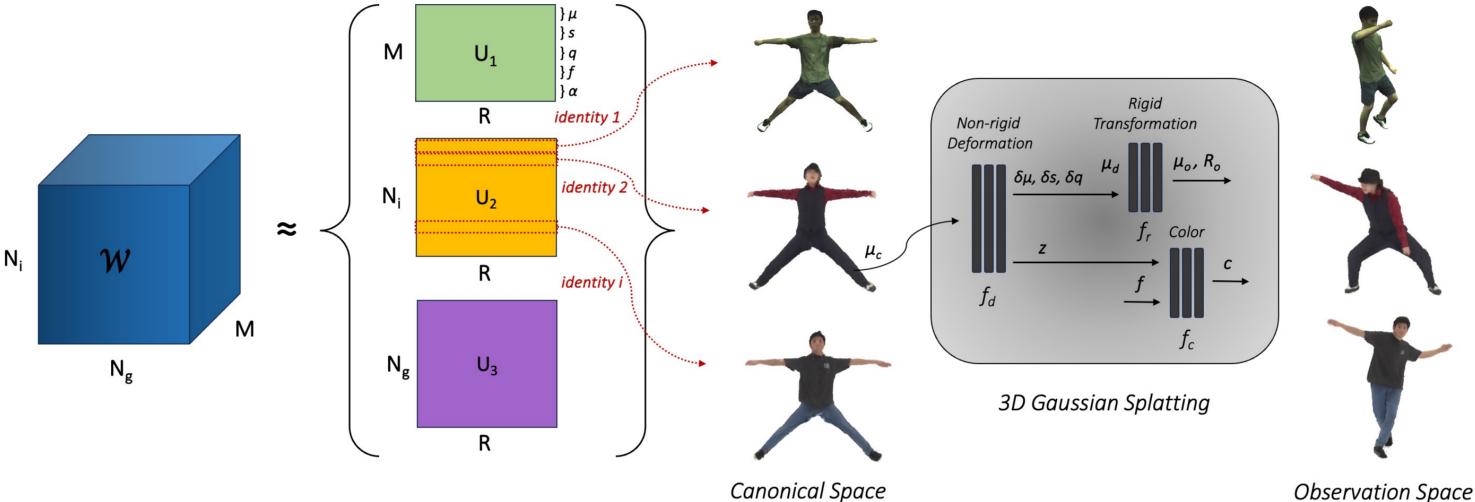


Multi-Identity Model (Ours)

Standard approaches learn multiple single-identity representations. We learn a *single* representation for *multiple* identities from monocular videos.

# Method

Tensor  ${oldsymbol{\mathcal{W}}}$ 



## Multi-Identity Representation with 3D Gaussian Splatting

**CP** Decomposition

For each identity i, we learn a set of 3D Gaussians  $\{G^{(i,g)}\}_{g=1}^{N_g}$ . Each Gaussian is associated with a position  $\boldsymbol{\mu}^{(i,g)} \in \mathbb{R}^3$ , a scaling vector  $\boldsymbol{s}^{(i,g)} \in \mathbb{R}^3$ , a quartenion  $\boldsymbol{q}^{(i,g)} \in \mathbb{R}^4$ , a feature vector  $\boldsymbol{f}^{(i,g)} \in \mathbb{R}^{32}$ , and an opacity  $\alpha^{(i,g)} \in \mathbb{R}$ . Given  $N_i$  identities, we construct a tensor:

Multi-Identity Training

$$oldsymbol{\mathcal{W}} \in \mathbb{R}^{N_i imes N_g imes M}, ext{where } oldsymbol{w}_{i,g,:} = \left[oldsymbol{\mu}^{(i,g)}; oldsymbol{s}^{(i,g)}; oldsymbol{q}^{(i,g)}; oldsymbol{f}^{(i,g)}; oldsymbol{\alpha}^{(i,g)}; oldsymbol{a}^{(i,g)}; oldsymbol{a}^{(i,g)}; oldsymbol{s}^{(i,g)}; oldsymbol{a}^{(i,g)}; oldsymbol{a}^{(i,g)};$$

We assume a low-rank structure and learn a **CP Tensor Decomposition** [1] with rank R:

$$m{W}_{(2)}pprox m{U}_3 \left(m{U}_2\odotm{U}_1
ight)^T$$
 , where  $m{W}_{(2)}\in\mathbb{R}^{N_g imes(N_iM)}$ 

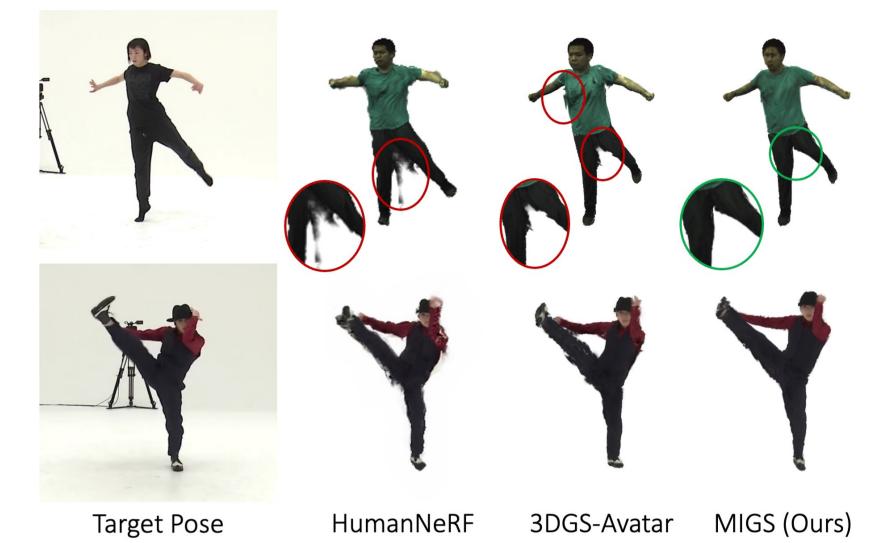
Learnable parameters:  $U_1 \in \mathbb{R}^{M \times R}$ ,  $U_2 \in \mathbb{R}^{N_i \times R}$ ,  $U_3 \in \mathbb{R}^{N_g \times R}$  i.e.,  $(M + N_i + N_g)R$  parameters instead of  $M N_i N_g$ .

For  $N_i = 30$ ,  $N_g = 5 \times 10^4$ , M = 43, R = 100, MIGS learns  $5 \times 10^6$  instead of  $6.5 \times 10^7$  parameters, leading to a decrease by at least one order of magnitude.

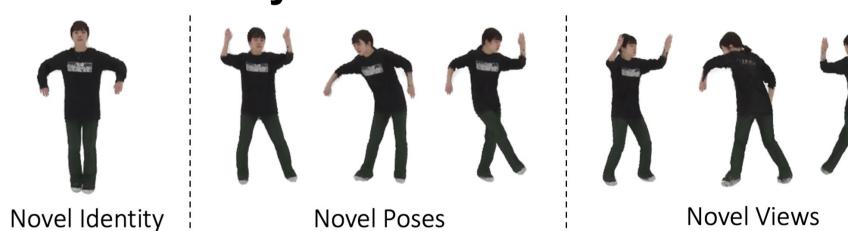
#### References

- [1] Kolda, T.G. and Bader, B.W., Tensor decompositions and applications, SIAM Review, 2009
- [2] Qian, Z. et al., 3DGS-Avatar: Animatable Avatars via Deformable 3D Gaussian Splatting, CVPR, 2024

## **Animation under Novel Poses**



## **Novel Identity**



## Ablation Study on Rank R and N<sub>i</sub>

