

# LASR: Learning Articulated Shape Reconstruction from a Monocular Video

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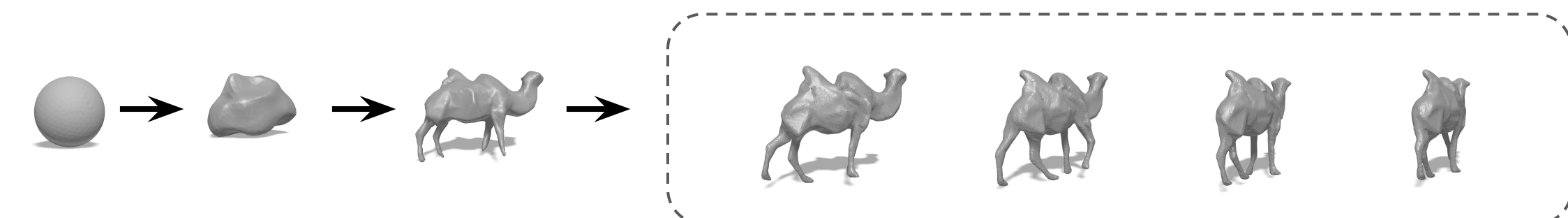


Research at Google

## Problem setup



Video of an object from arbitrary category



Articulated 3D shape reconstruction

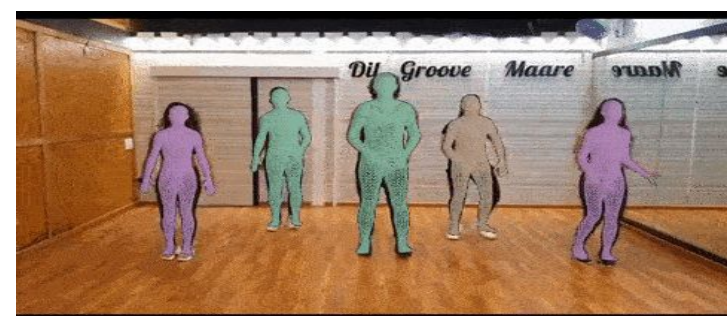
### Challenges

- “2 x N points x T” vs “3 x N x T + camera pose + intrinsics”
  - The problem is under-constrained due to the time-varying 3D shape.
  - Difficult to obtain accurate 2D point trajectories.

“3 x N + camera pose + intrinsics” for SfM

## Related work

### Template-based



Parametric shape-pose models (SMPL, SMAL)  
e.g., SMPLify, VIBE [1]



Weakly-supervised category shape reconstruction  
e.g., CMR, A-CSM, UMR, UCMR [2]



NRSfM,  
e.g., ND-NRSfM, C3DPO [3]



LASR (Ours)

### Template-free

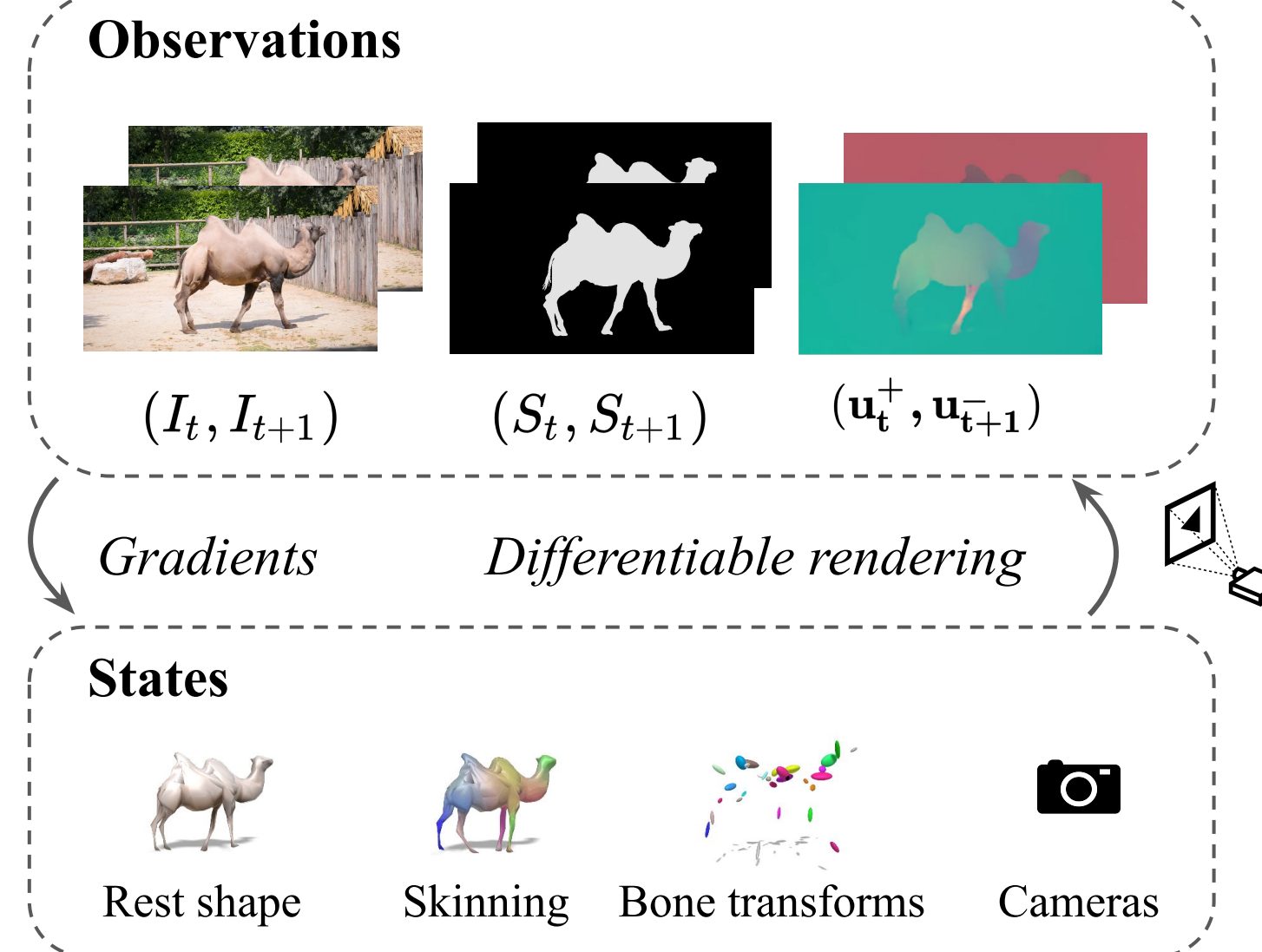
- [1] Muhammed, Athanasiou, and Black. "VIBE: Video inference for human body pose and shape estimation." CVPR 2020.  
[2] Goel, Kanazawa, and Malik. "Shape and viewpoint without keypoints." ECCV 2020.  
[3] David, et al. "C3DPO: Canonical 3d pose networks for non-rigid structure from motion." ICCV 2019.

LASR reconstructs articulated 3D shapes from a single video by differentiable rendering with data-driven motion correspondence priors.

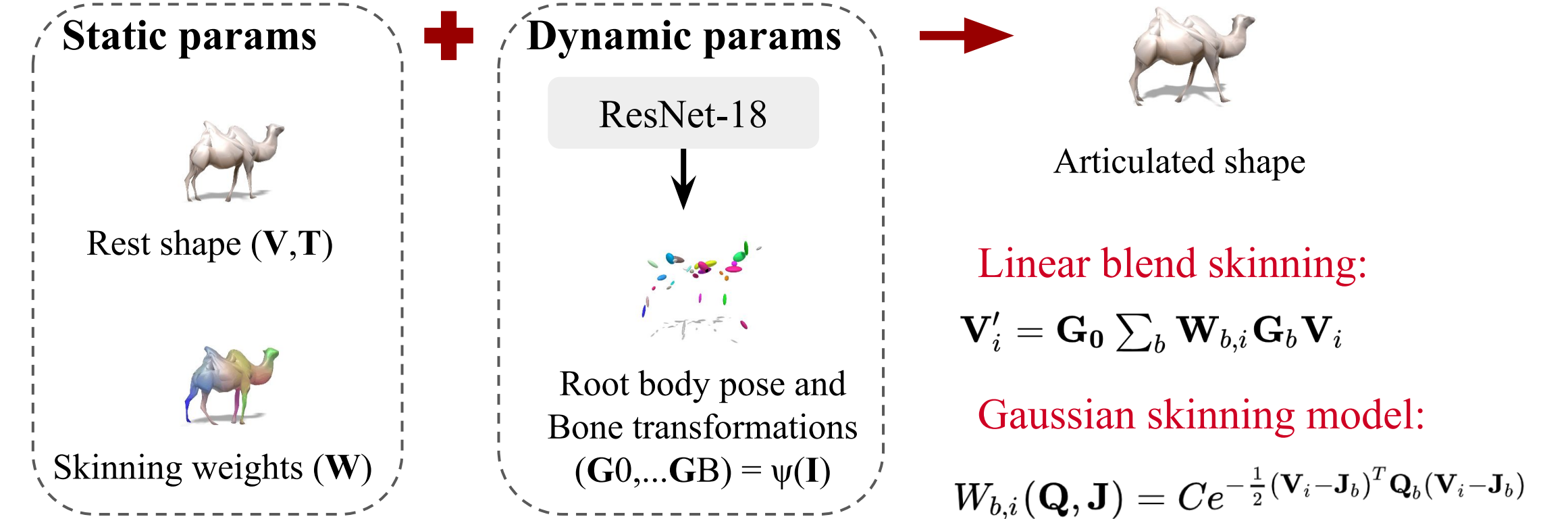
Code at <http://lasr-google.github.io/>.

## Approach

Key idea: diff. rendering to fit pixels, masks, and flow



### Articulation modeling

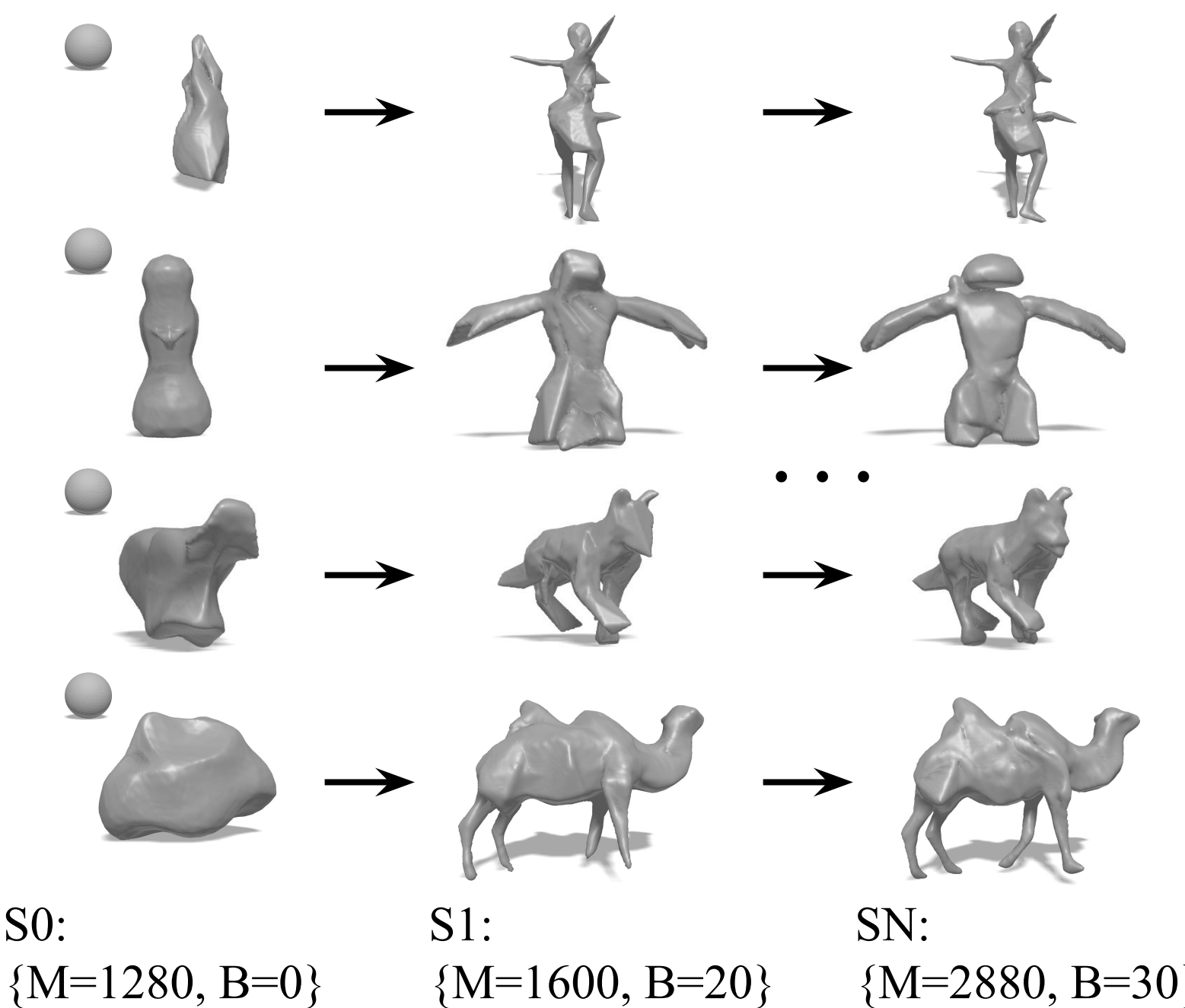


### Objective

$$L(V, T, W, K, \psi) = L_{\text{recon}} + L_{\text{reg}} \begin{cases} L_{\text{recon}} = L_{\text{mask}} + L_{\text{flow}} + L_{\text{color}} \\ L_{\text{reg}} = L_{\text{shape}} + L_{\text{ARAP}} + L_{\text{least-motion}} + L_{\text{symmetry}} \end{cases}$$

intrinsic

## Coarse-to-fine optimization



## Results

