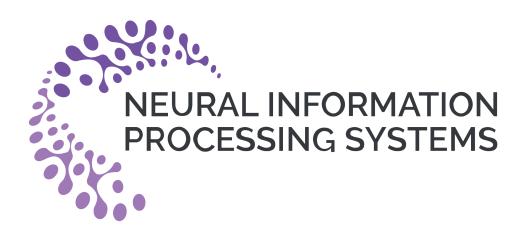
Geometry-aware Two-scale PIFu Representation for Human Reconstruction

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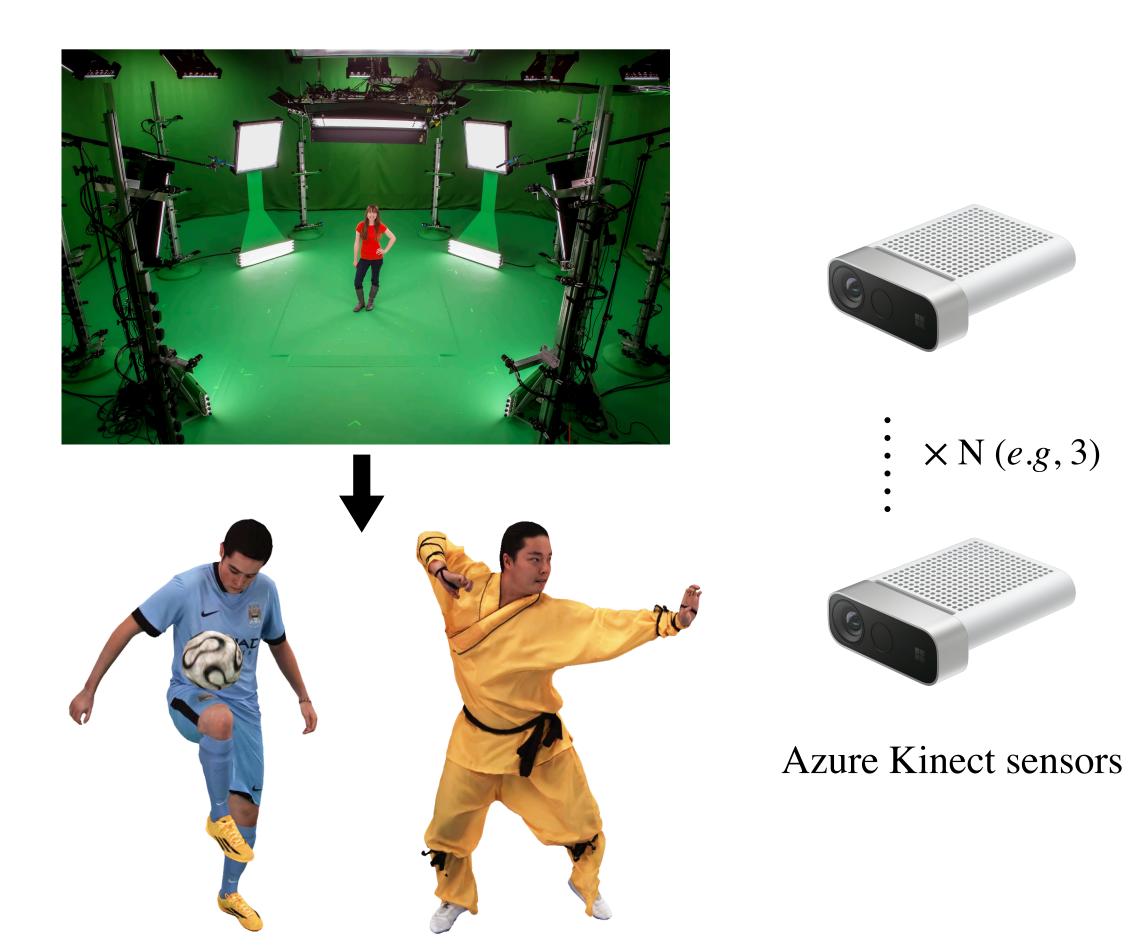






Our Goal

Reconstruct high-quality human models in a sparse (e.g., 3 RGBD sensors) capture setting.



Capturing is Expensive

Collet et al. High-quality streamable free-viewpoint video (ACM TOG 2015)

N : number of views RGB Images \times N (*e.g.*, 3) . . . 3D human model

Depth Maps \times N (*e.g.*, 3)

Users Friendly

THuman2.0-Dataset : https://github.com/ytrock/THuman2.0-Dataset



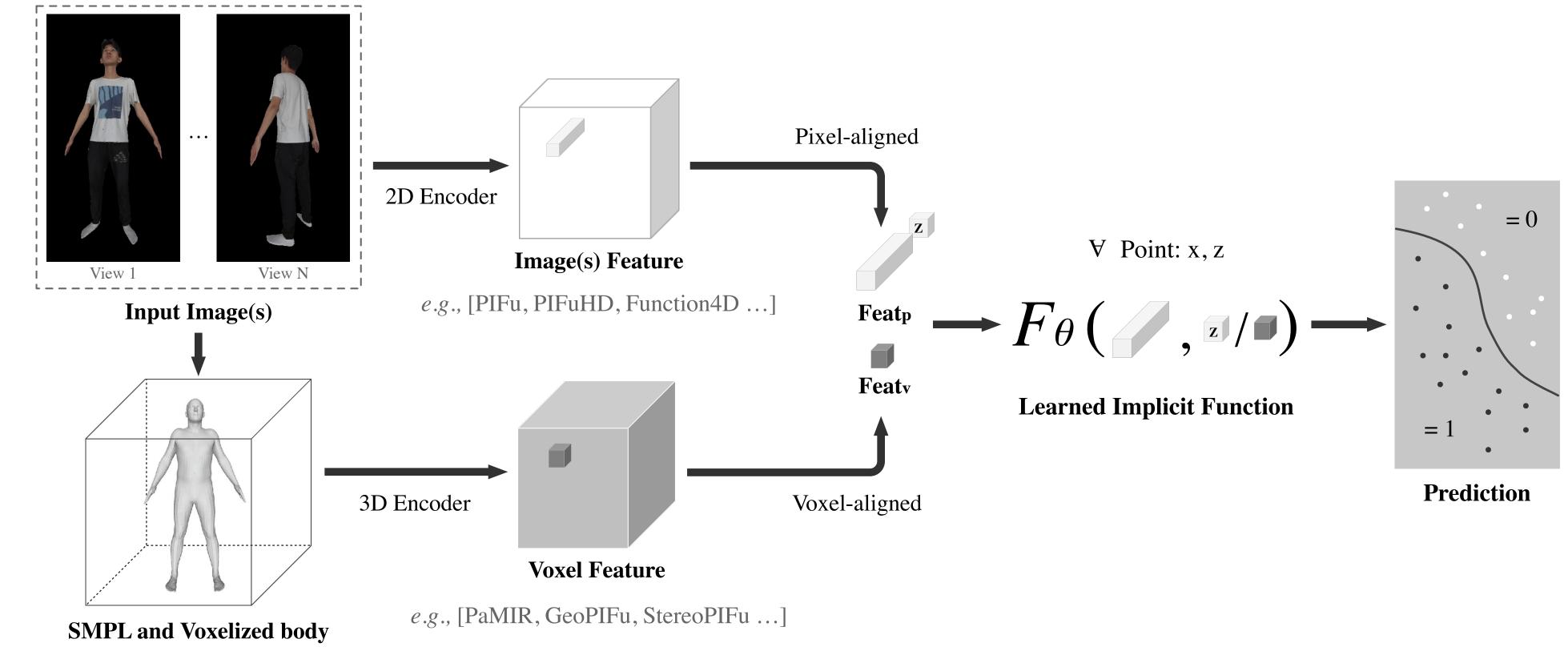




Human Reconstruction from Very Sparse Views

deep learning-based methods are applied to human reconstruction.

- Explicit shape regression : SiCloPe [CVPR 2019], DeepHuman [ICCV 2019], NormalGAN [ECCV 2020] ...
- Learning Implicit fields : PIFu [ICCV 2019], StereoPIFu [CVPR 2021], Function4D [CVPR 2021] ...



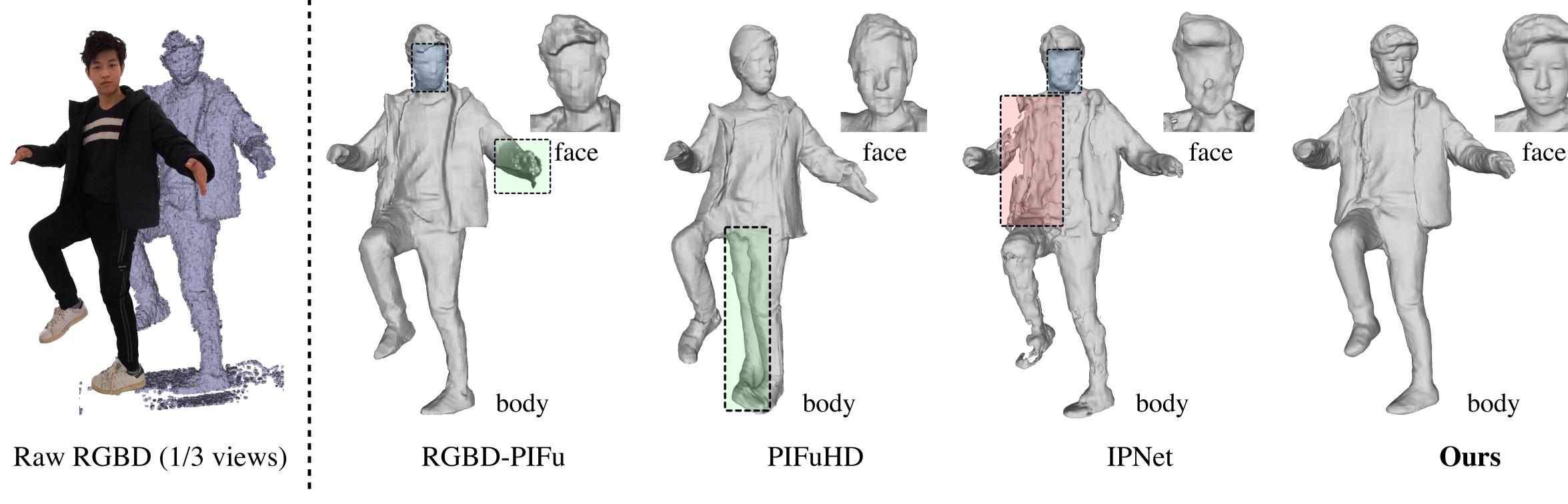
Human reconstruction from pixels (RGB, Depth) in an implicit manner

Due to ill-posed properties (e.g., severe occlusion, input noise) in the very sparse capture settings,



Our Observations and Contributions

- Body geometries with topology errors (depth noise is amplified under sparse views)
- Lack of high-frequency details (*e.g.*, Flat or incorrect facial surfaces, hair geometries)



The reconstructed quality of the existing implicit methods is still unsatisfactory under the sparse capture settings.

Saito et al. PIFu : Pixel-aligned implicit function for high-resolution clothed human digitization (ICCV 2019) Saito et al. PIFuHD : Multi-level pixel-aligned implicit function for high-resolution 3d human digitization (CVPR 2020) Bhatnagar et al. Combining implicit function learning and parametric models for 3d human reconstruction (ECCV 2020)

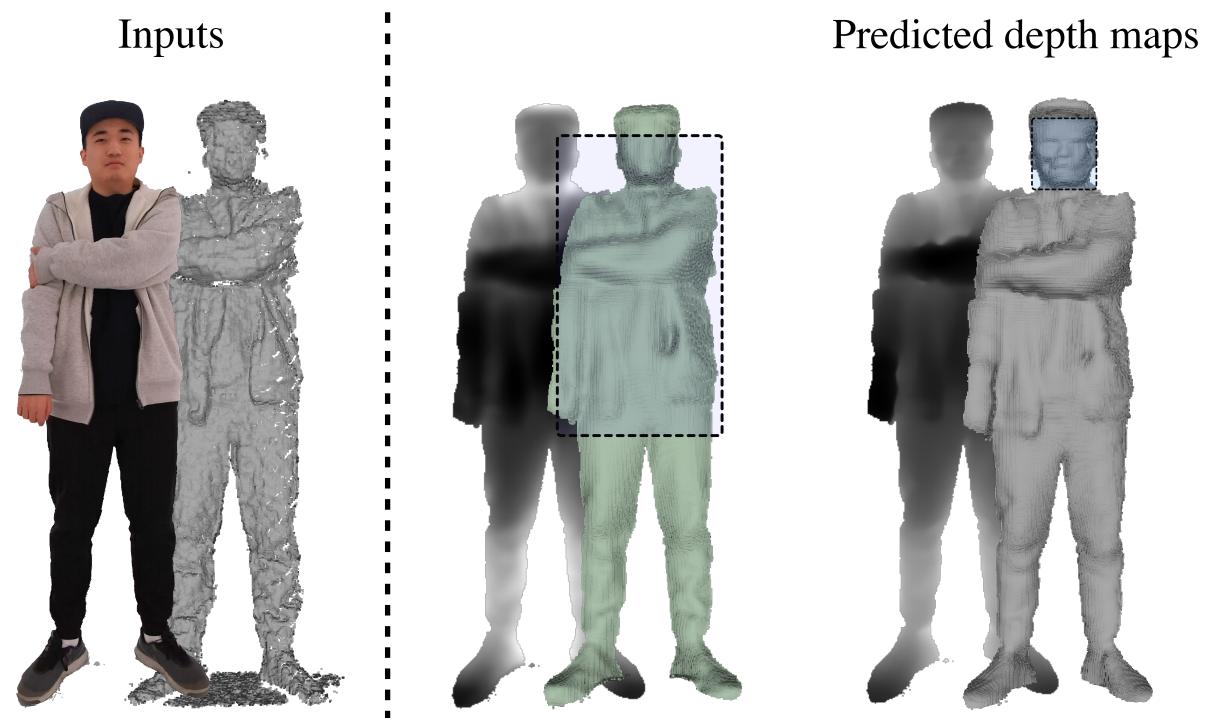




Multi-task Formulation

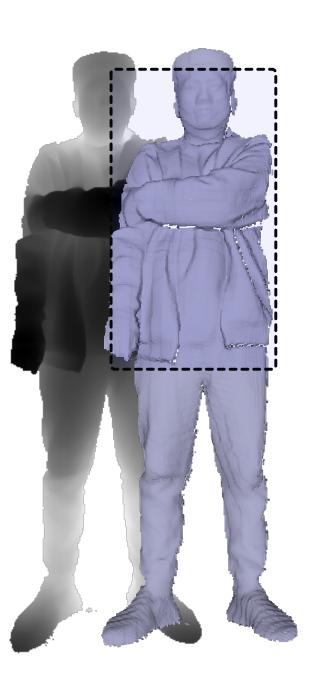
The two tasks, depth denoising and 3D reconstruction are complementary to each other.

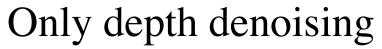
- Image-to-image depth denoising : preserves local geometric fidelity, prone to introducing incorrect details
- PIFu-based **3D** reconstruction : provides global topology guidance, lacking high-frequency local details



Raw RGBD (1/3 views)

Only reconstruction





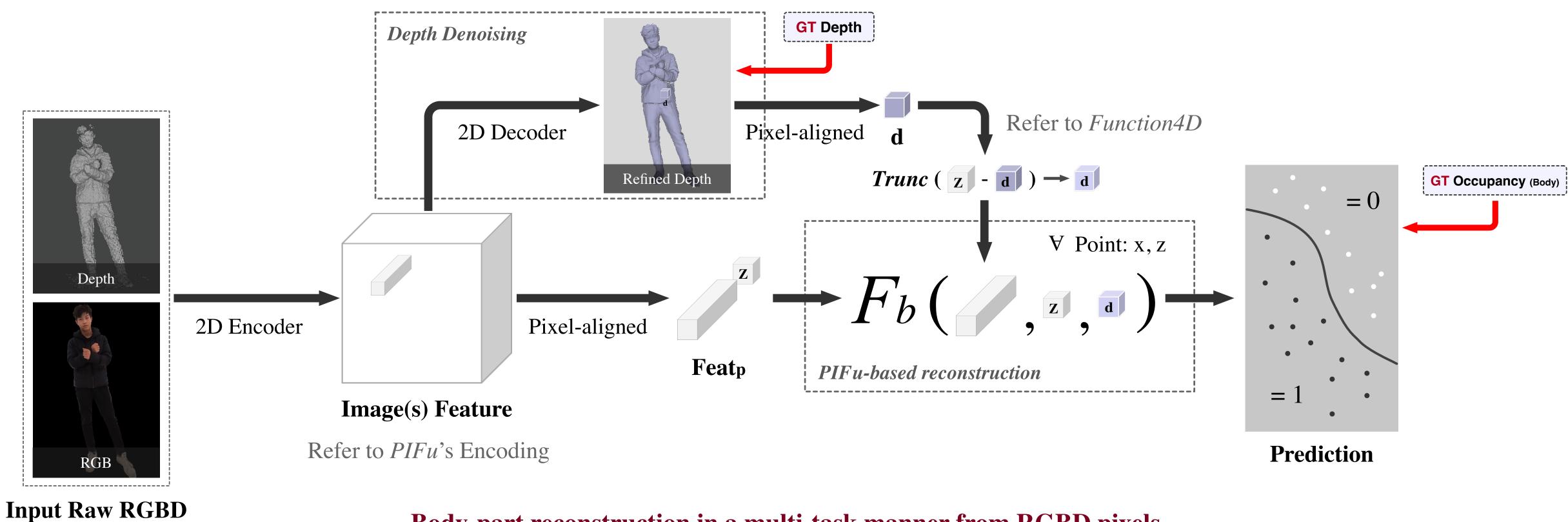
Multi-task manner



Multi-task Formulation

exploit their complementary properties.

• **Depth denoising** and **Occupancy estimation** tasks share the image(s) features



Yu et al. Function4D: Real-time Human Volumetric Capture from Very Sparse Consumer RGBD Sensors (CVPR 2021)

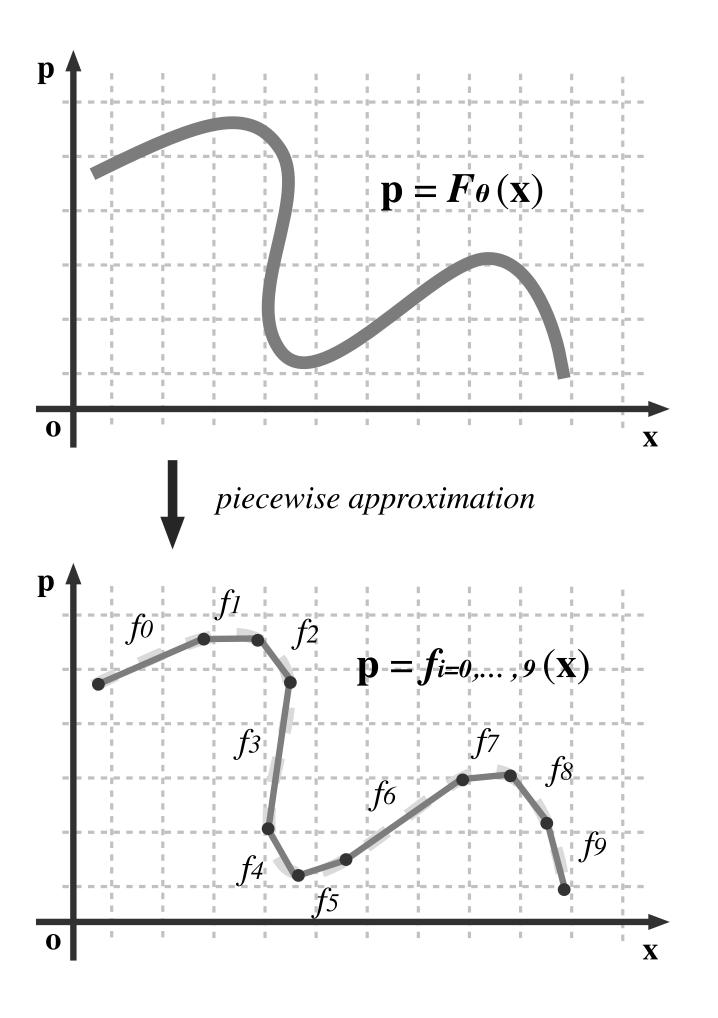
Proposed : formulate **depth denoising** and **body reconstruction** processes in a multi-task learning manner to

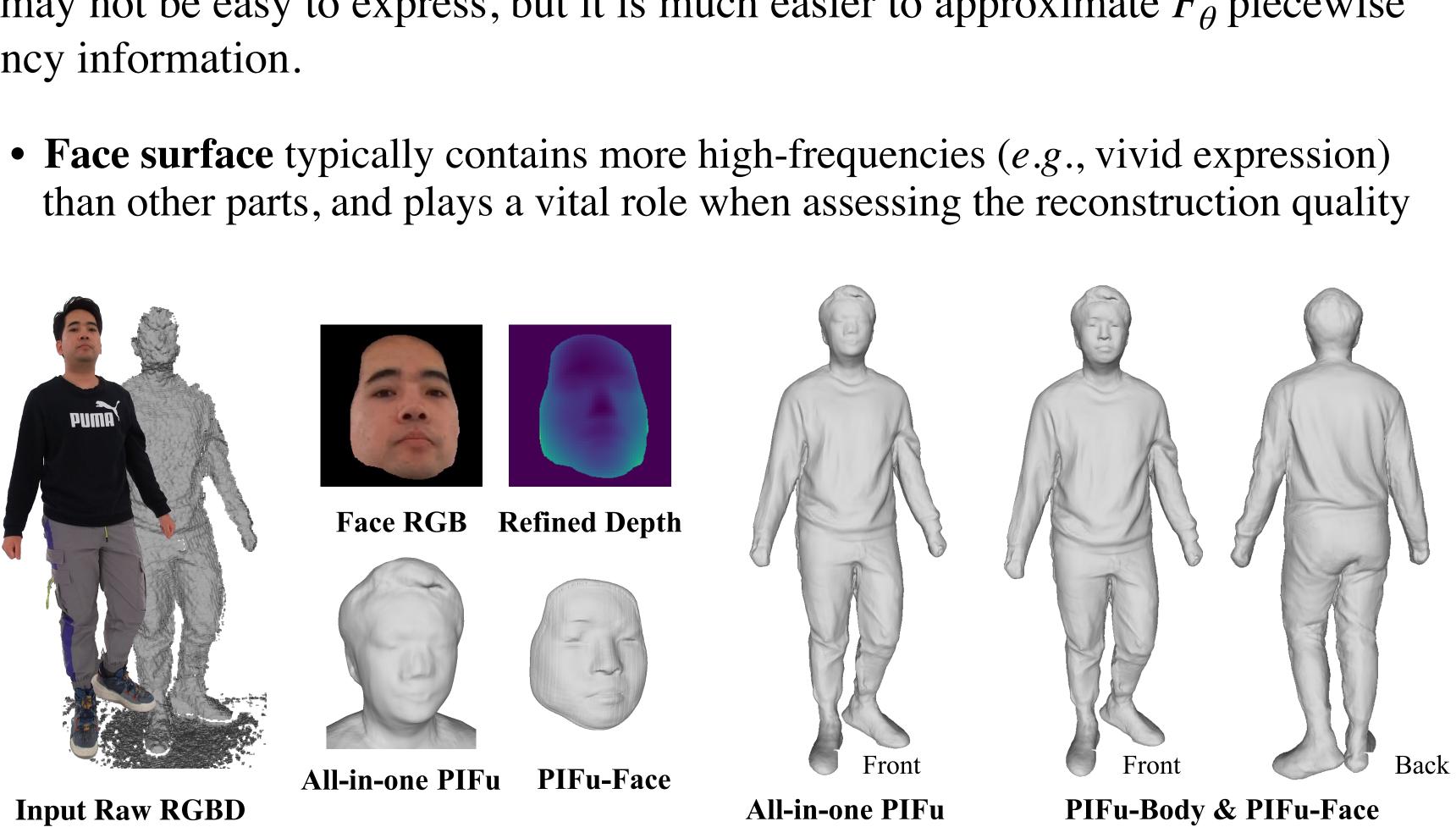
Body-part reconstruction in a multi-task manner from RGBD pixels



PIFu-Body and PIFu-Face

A function F_{θ} of high complexity may not be easy to express, but it is much easier to approximate F_{θ} piecewise (e.g., in two parts) for high-frequency information.



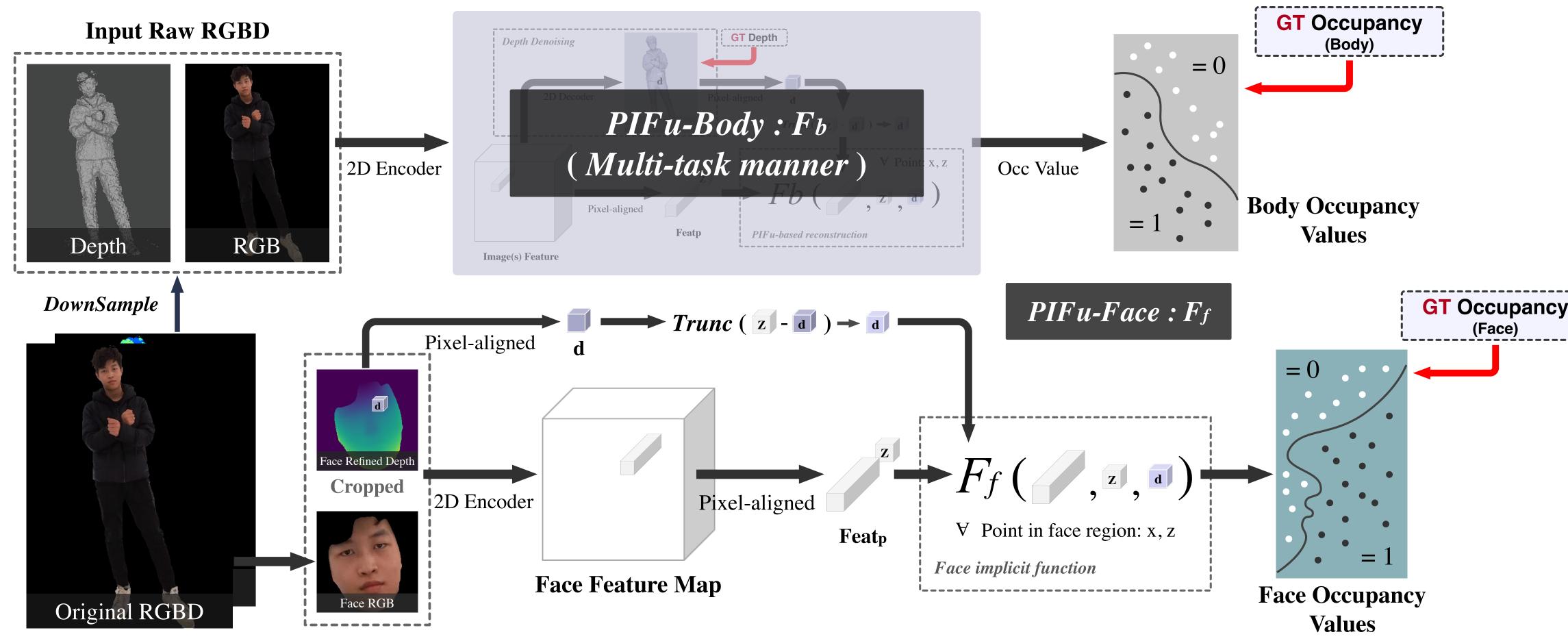


Face and body reconstruction based on piecewise (two parts) approximation

PIFu-Body and PIFu-Face

Proposed : express the implicit function F_{θ} in a **piecewise manner** (*i.e.*, PIFu-Body: F_{b} and PIFu-Face: F_{f}) to reduce the complexity of joint occupancy estimation while producing vivid facial and body details.

- The PIFu-Face F_f is conditioned on the high-resolution face image and the denoised facial depth map
- F_f can be pretrained on the existed 3d Face Dataset (e.g., FaceScape) to introduce stronger priors



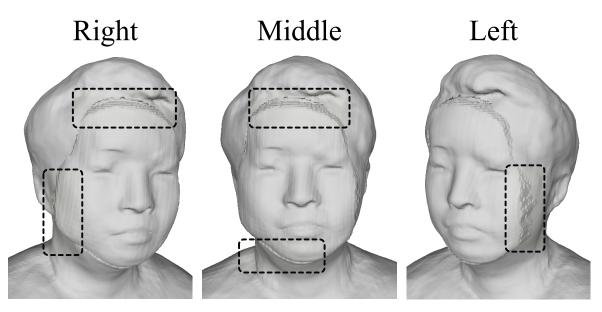




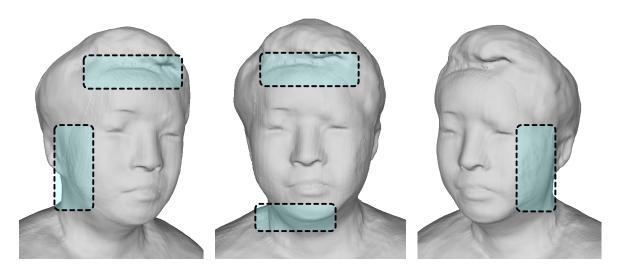
Face-to-body Occupancy Fields Fusion

Simply merging the reconstructed face and body (*i.e.*, replacing body occupancy value : o_h with face occupancy value : o_f for the facial points) would result in the discontinuity artifacts at the stitching. **Proposed** : fuse the face and body occupancy fields (O_b, O_f) via adaptive weights ω calculated in 3D space.

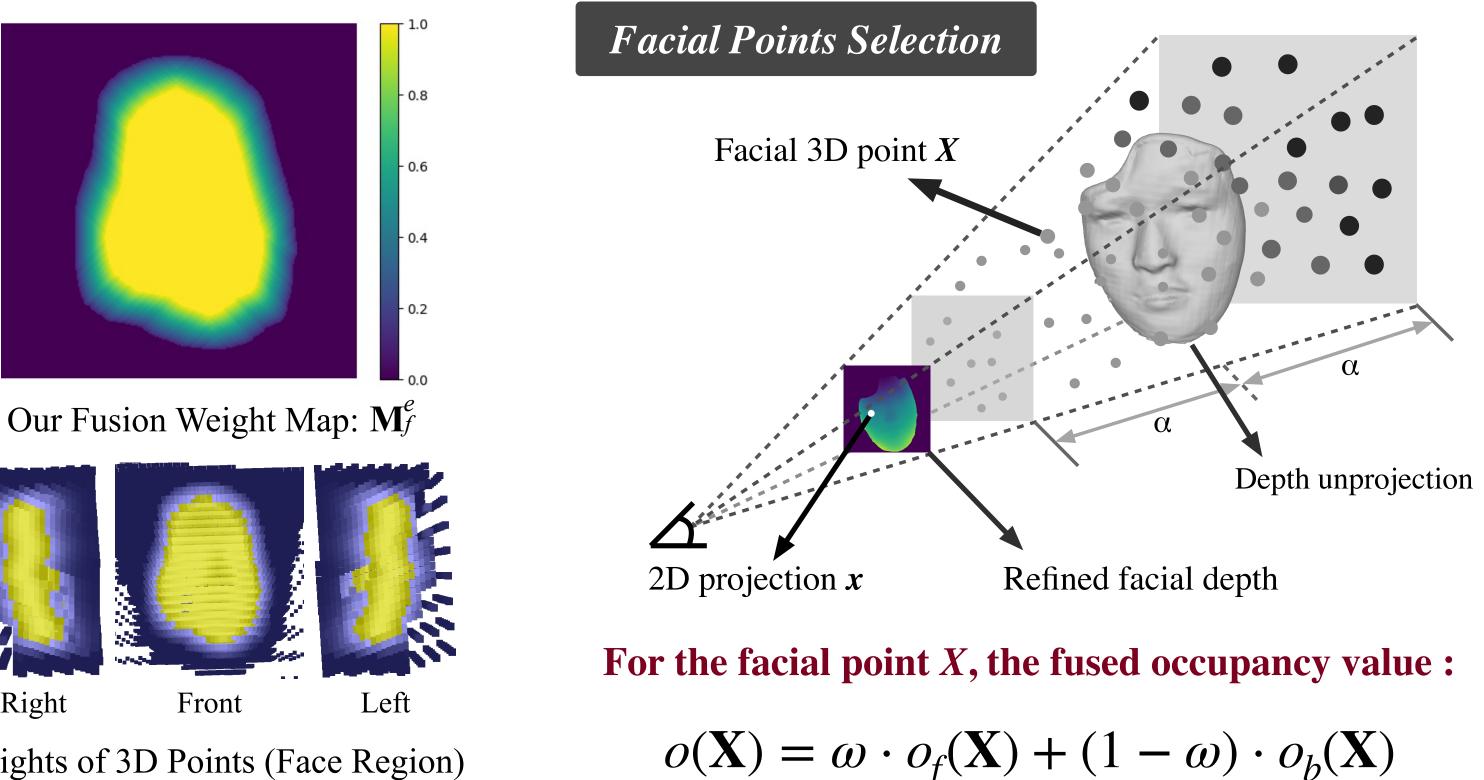
In x-y plane, compute a 2D fusion weight map via eroding edges of the facial mask II. Along z axis, compute the weights through a Gaussian distribution model of the PSDF values

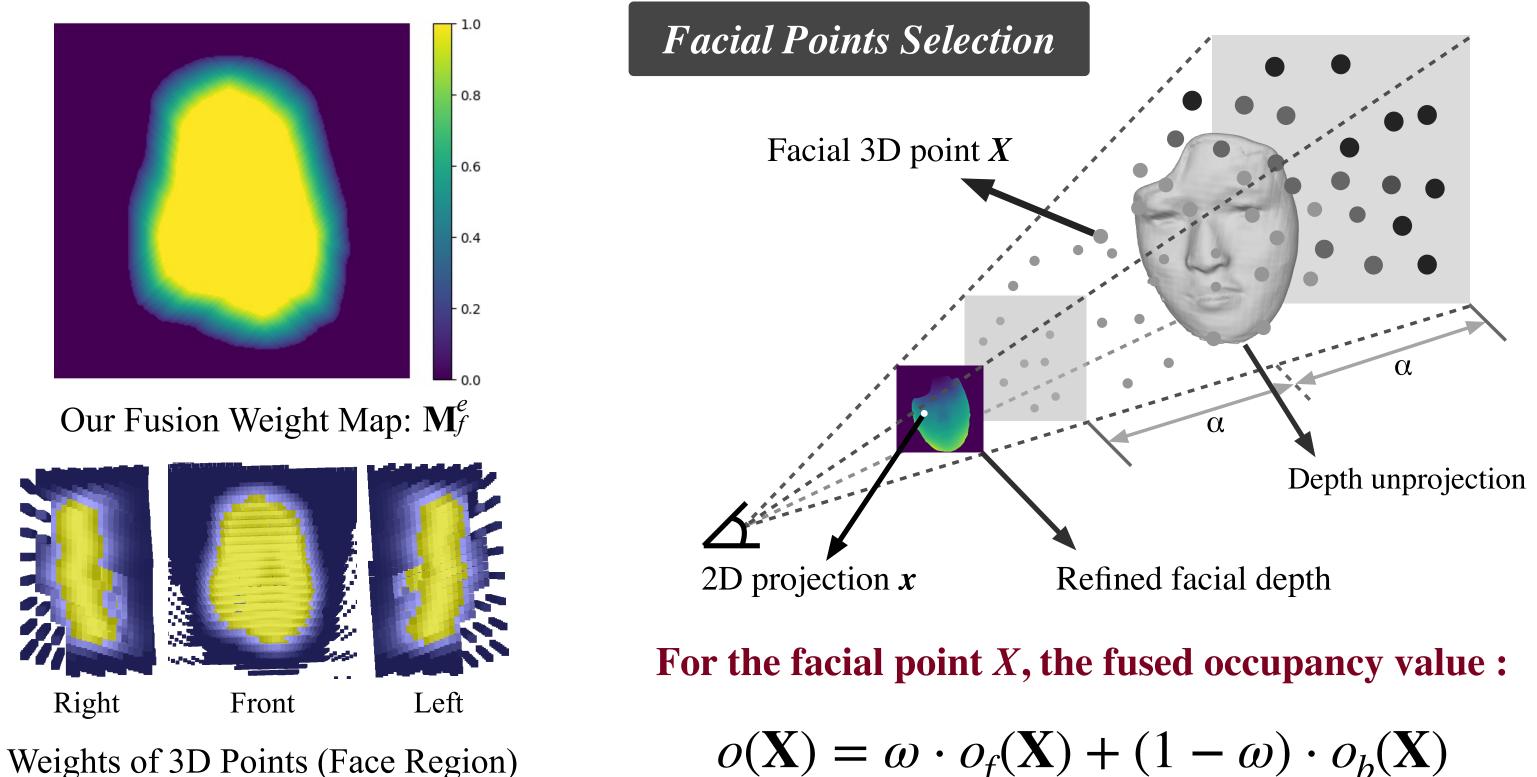


Simply merging face and body



Adaptive face-to-body Fusion (**Ours**)

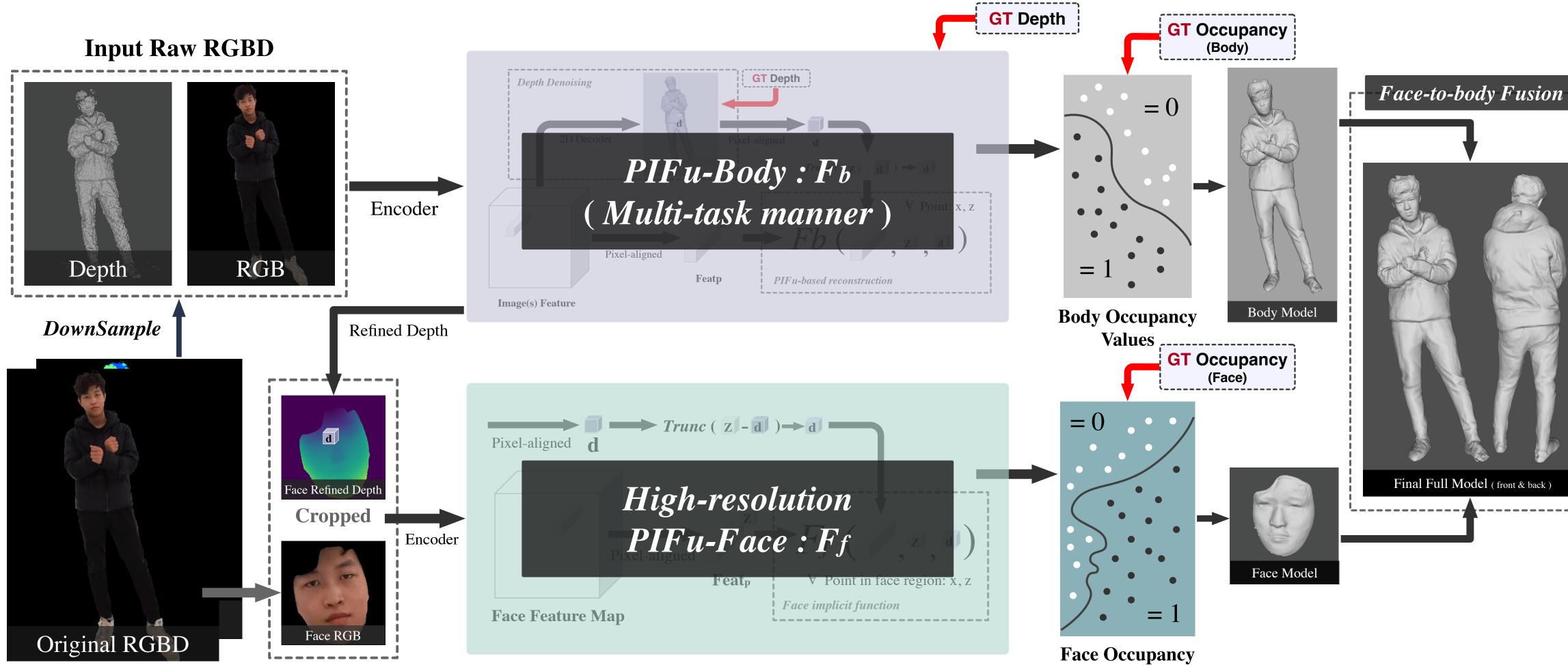






Pipeline Overview

I. PIFu-Body : F_b predicts the body field O_b and the refined depth maps from sparse and noisy RGBDs II. PIFu-Face : F_f obtains the fine-grained face field O_f , using the refined depth from F_b and the high-resolution face RGB III. Face-to-body Fusion : W reconstructs full human model by fusing O_b and O_f



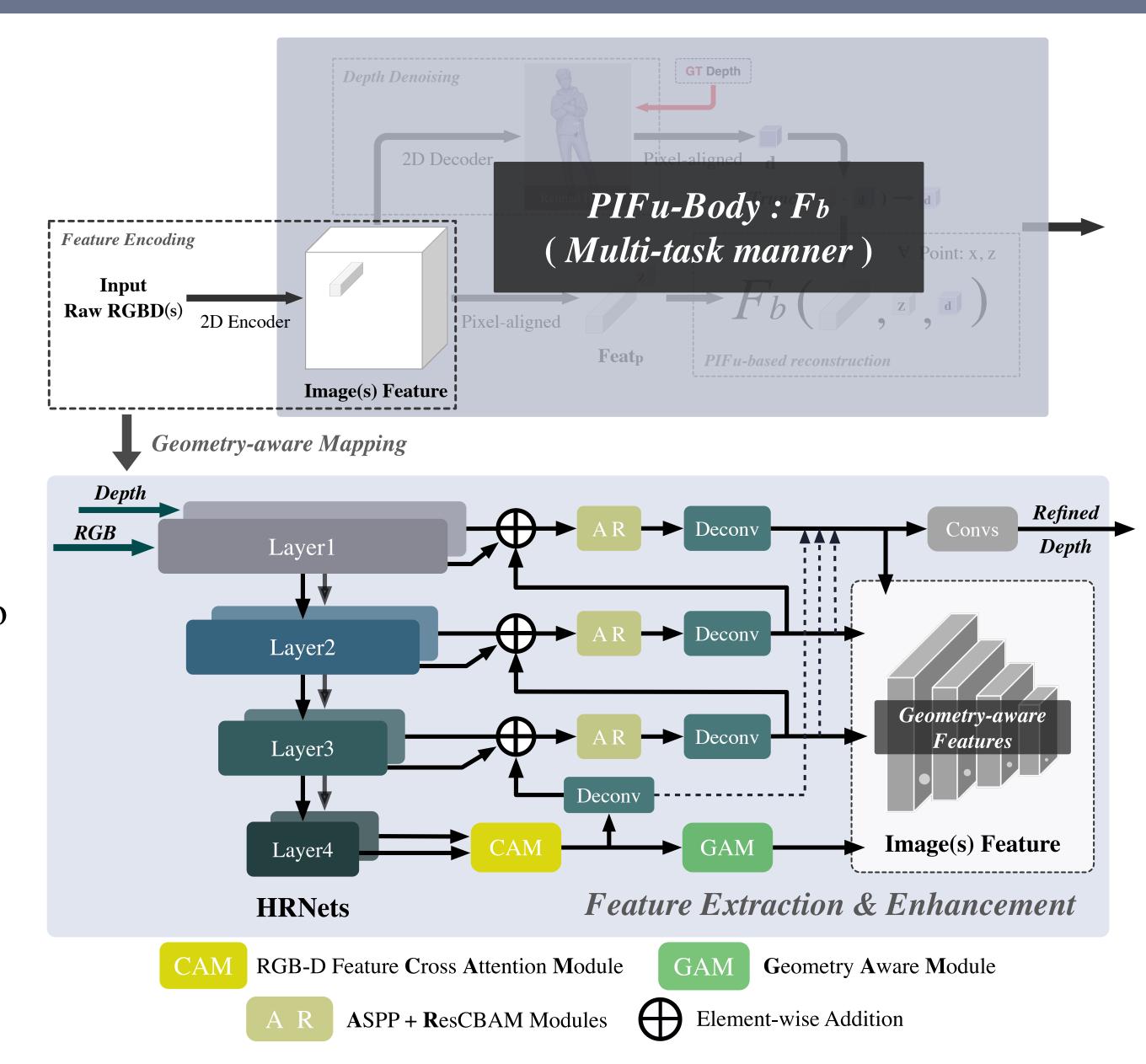
Face Occupancy Values



Geometry-aware Features

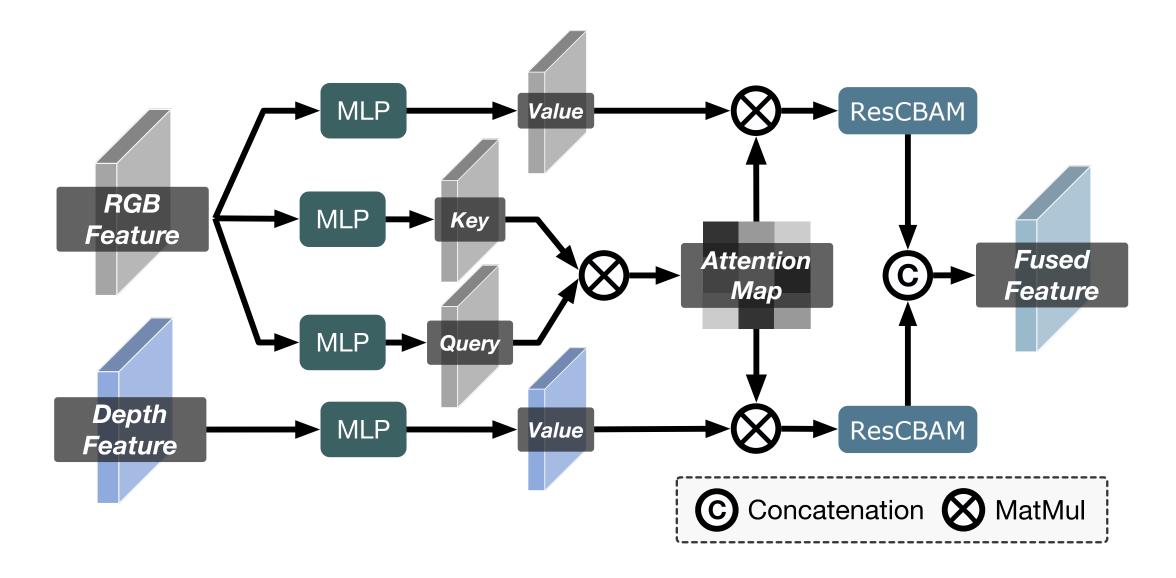
The encoded image(s) features aim to exploit the complementary properties of depth denoising and occupancy field estimation.

- Two *HRNets* are used to encode the RGB and Depth data respectively for handling modal discrepancy
- A novel **Cross Attention Module** (CAM) is proposed to fuse RGB and Depth top-level backbone features
- A novel **Geometry Aware Module** (GAM) is proposed to enrich the CAM output features with high-frequency information
- The enhanced features and the fused low-level features form the **Geometry-aware Features**



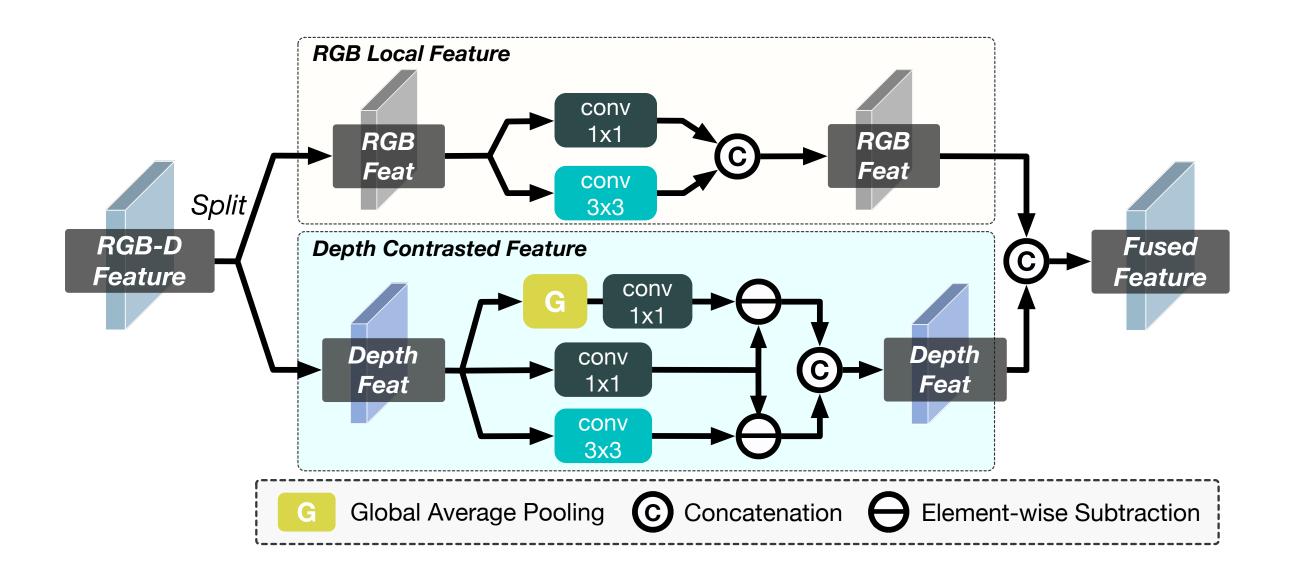
CAM and GAM

Cross Attention Module (CAM)



• Fuse the RGB and depth features by computing their non-local correlations

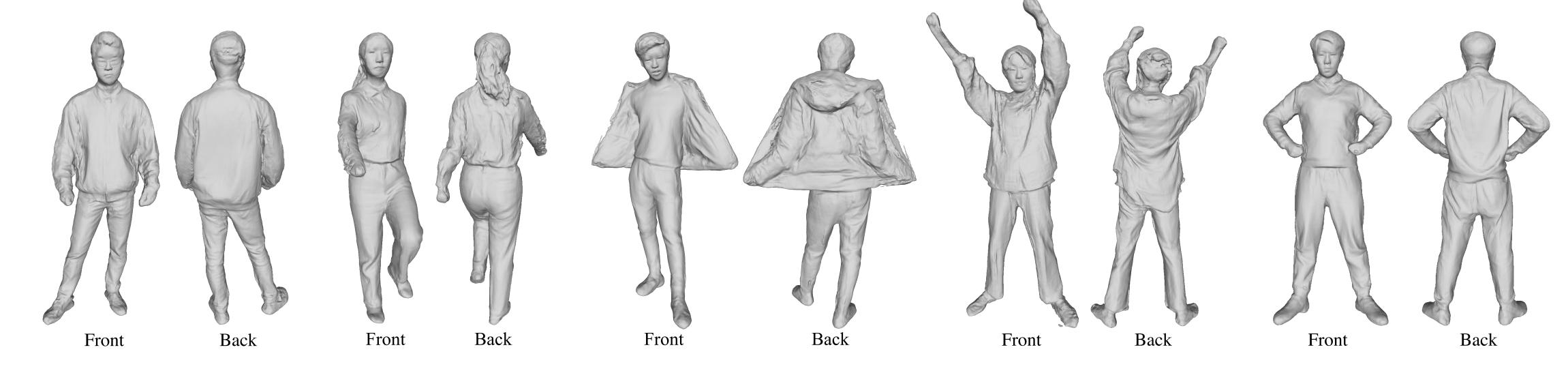
Geometry Aware Module (GAM)



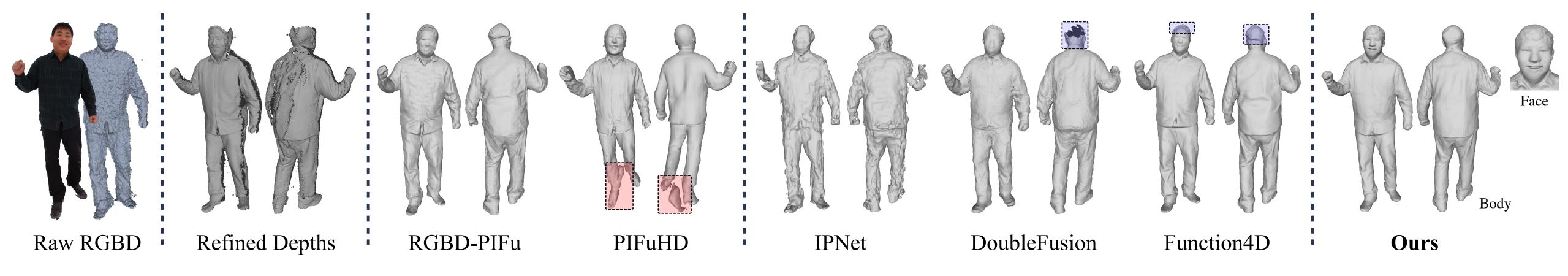
• Calculate the depth contrasted features to enrich the fused features with high-frequency information

Results

Our reconstructed results under various poses of different human bodies :



Qualitative comparisons on our captured real data :

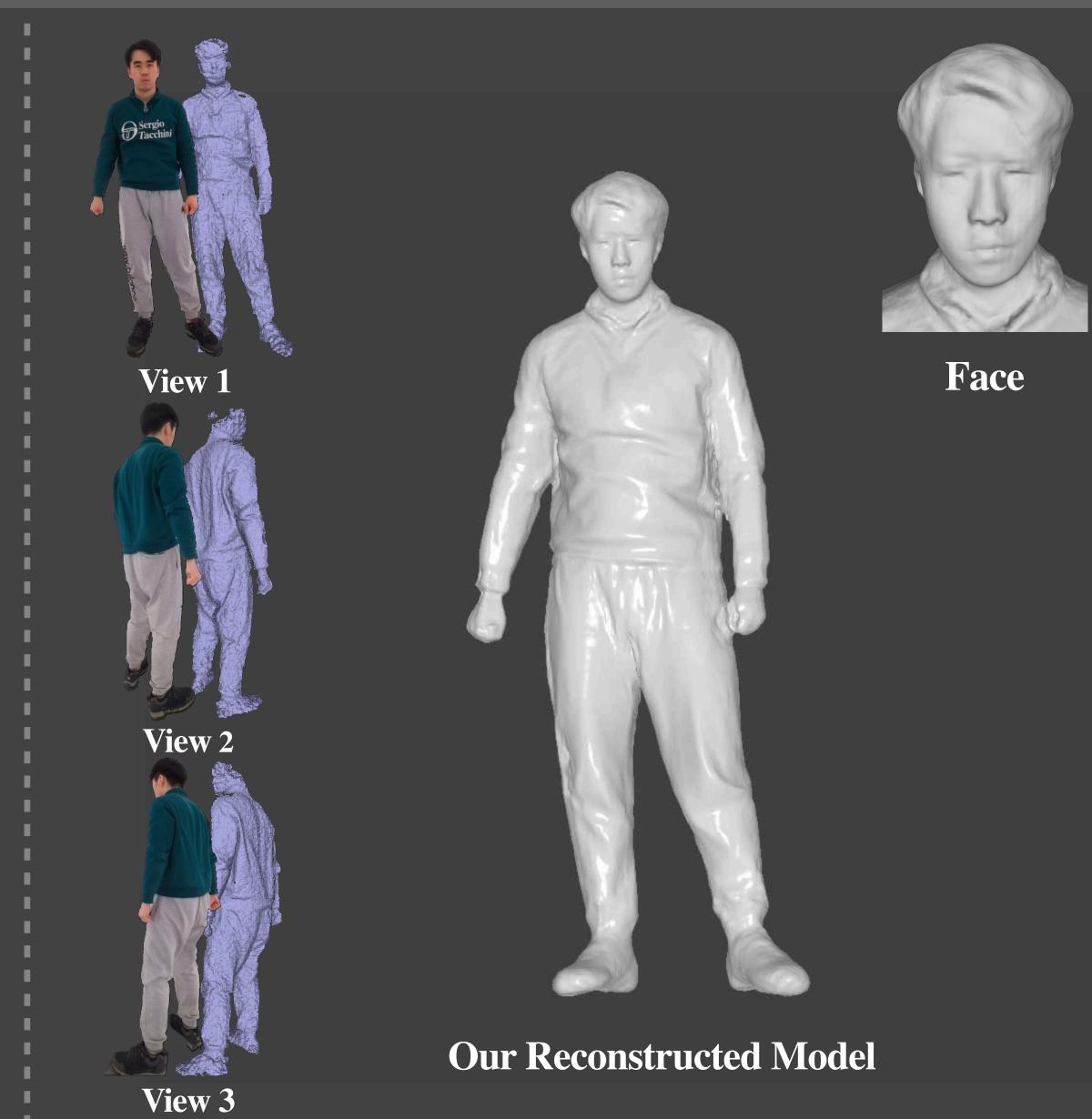


Refer to our paper for more experiments and results

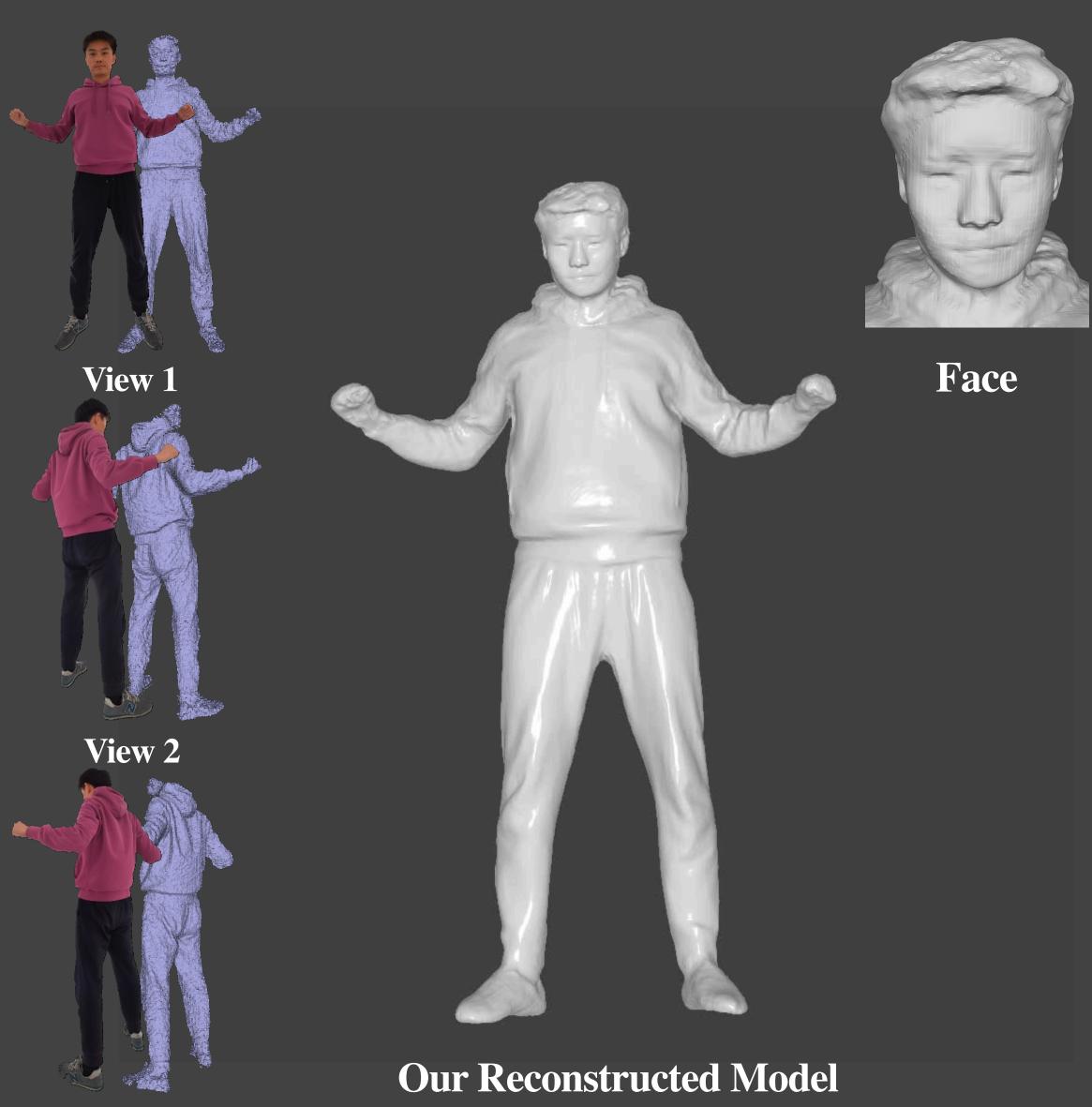




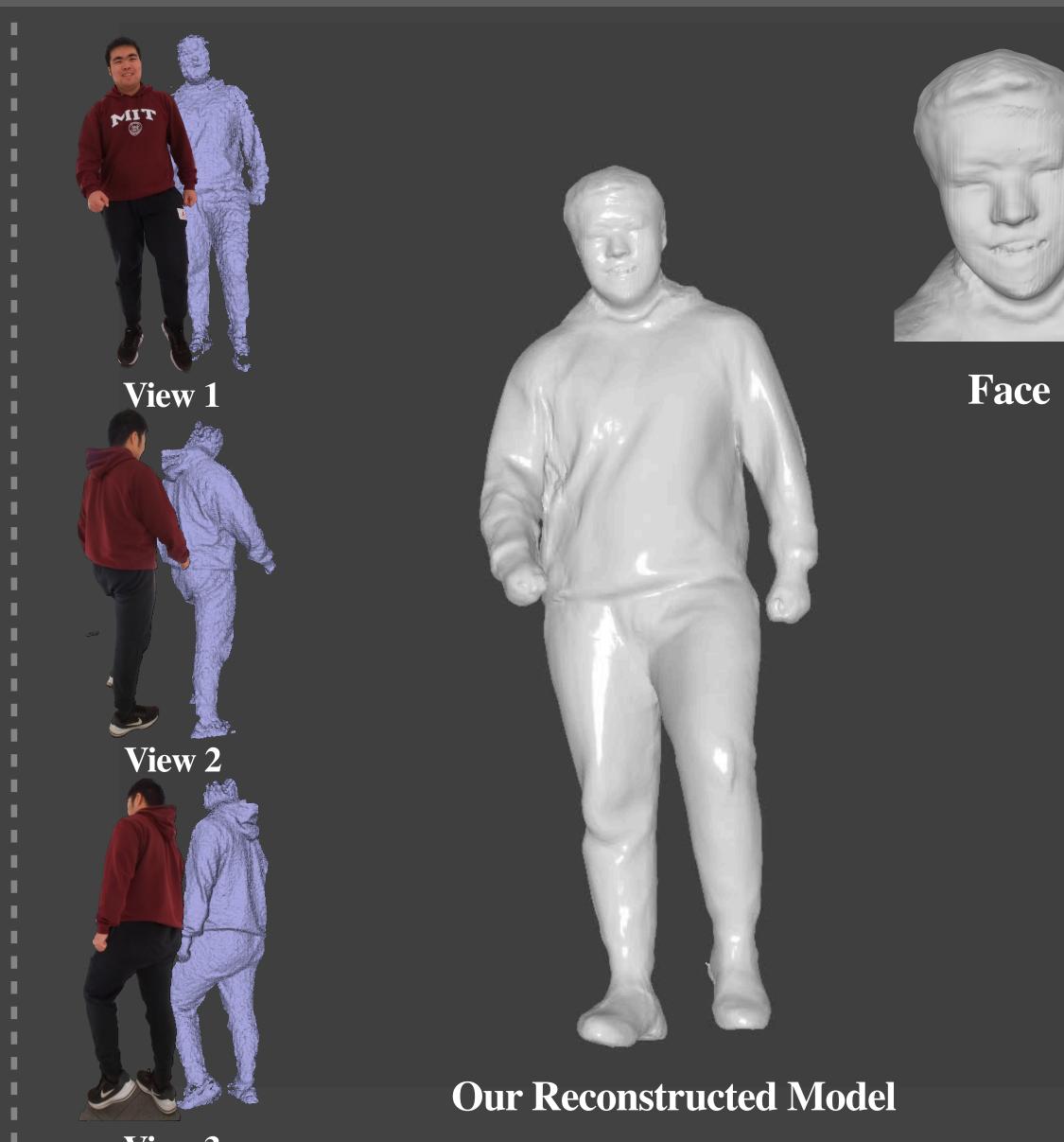








View 3



View 3



Thank you for watching !

