Computer Vision Group
TUM Department of Informatics
Technical University of Munich

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Seminar:
Recent Advances in 3D Computer Vision

Computer Vision Group

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Paper:
Texture and Geometry Optimization for RGB-D Reconstruction

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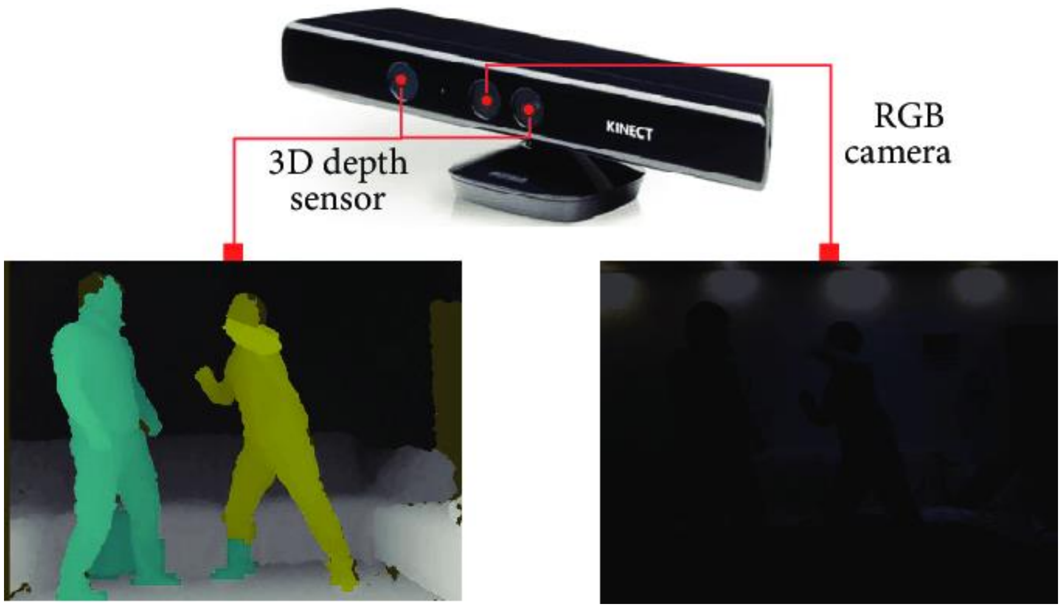
What is RGB-D?

- RGB-D stands for…

- A RGB device looks like…

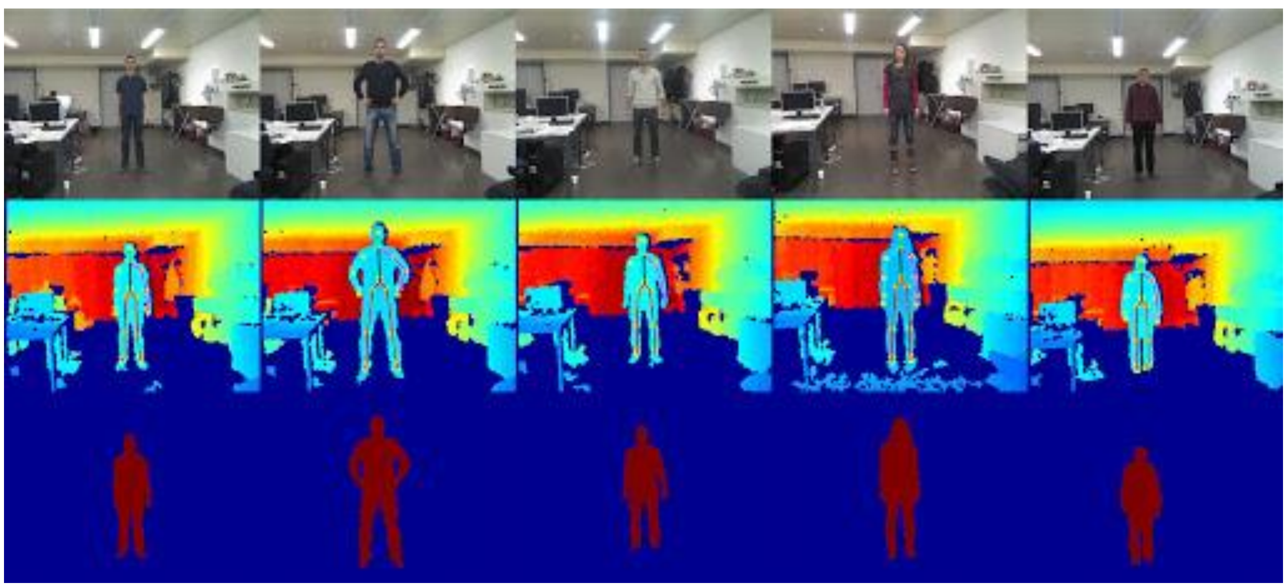


What is RGB-D?

RGB Image

Depth Image

Microsoft Kinect

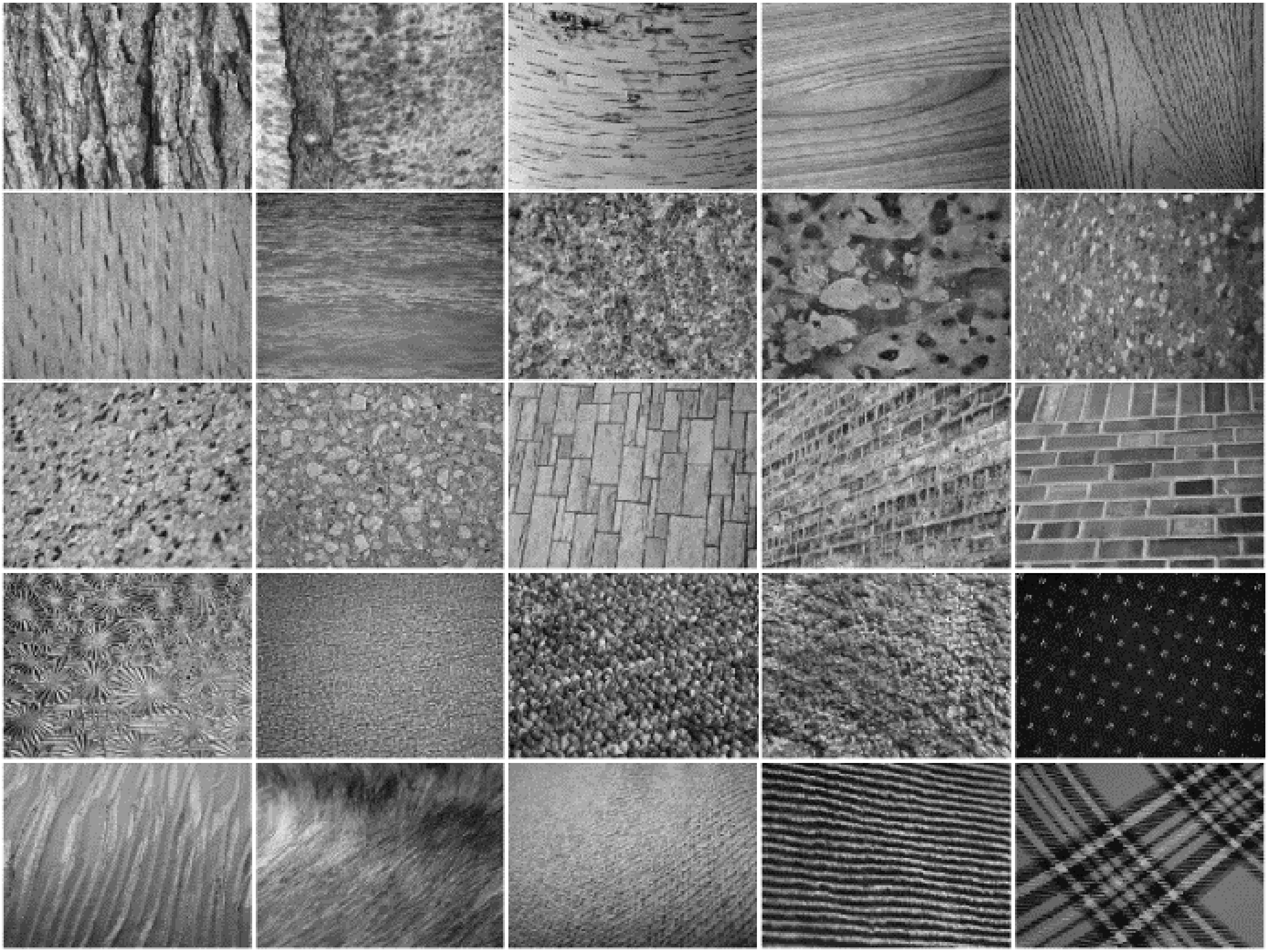


- An example Dataset of RGB-D

Requirements

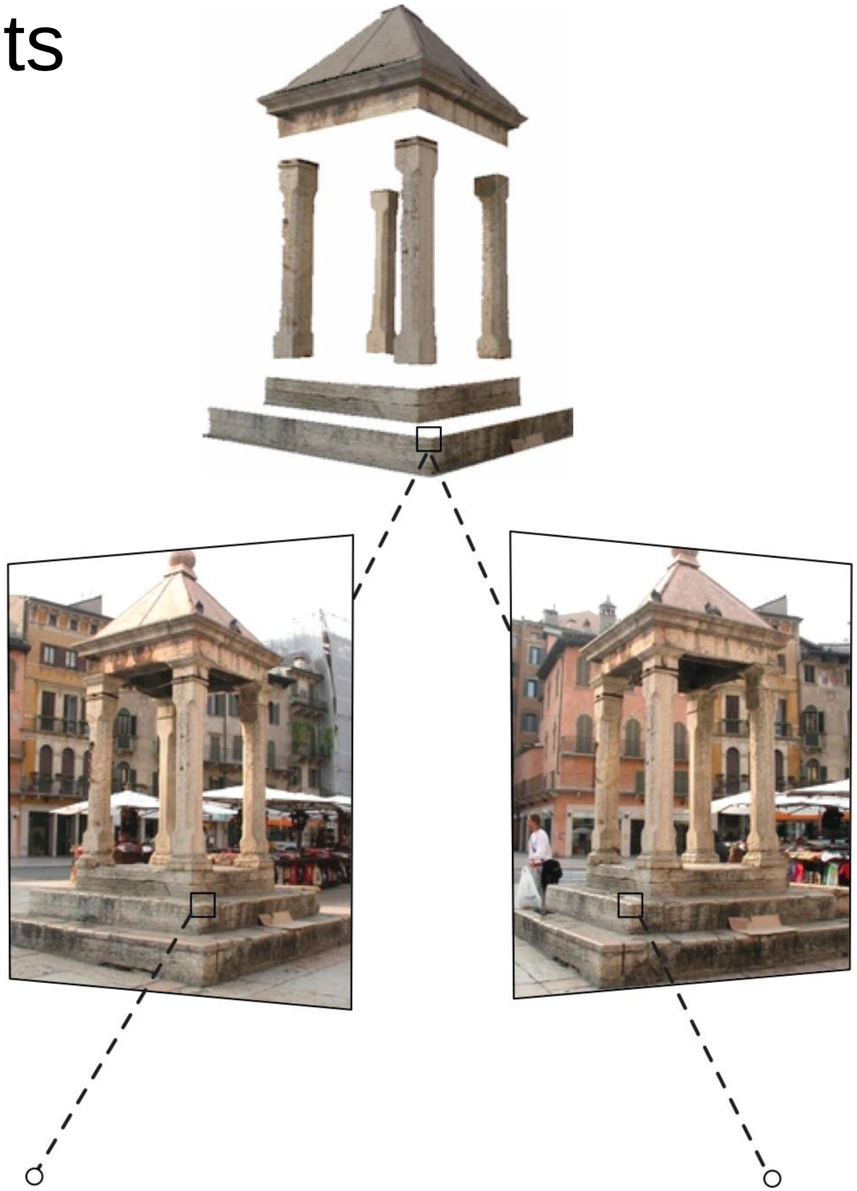
- A high-quality 3D reconstructed model via the RGB-D sensor should reach two basic requirements, correct geometry and high-fidelity texture.

Requirements



- Texture: Sample images from UIUC texture dataset

Requirements



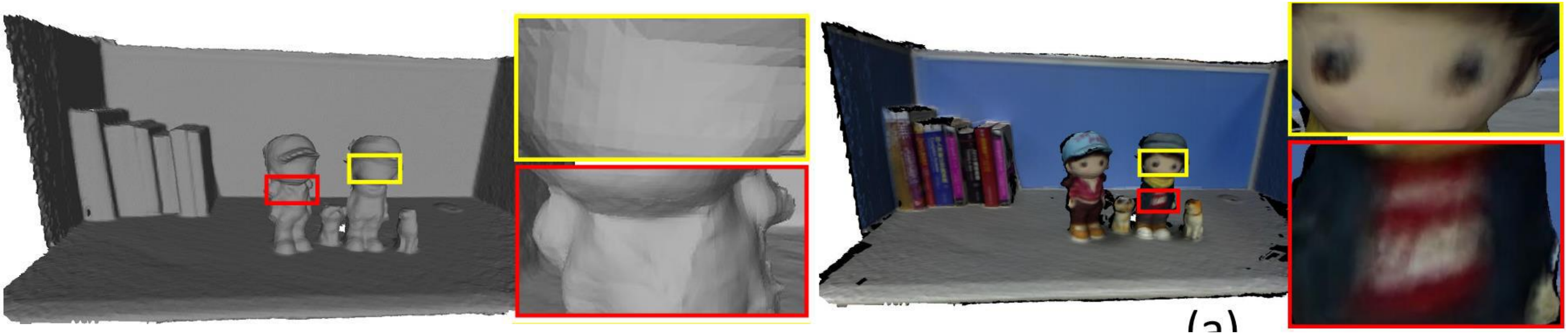
- Geometry: Two perspective views of the same 3-D scene

Problems

The high-quality geometry and high-fidelity texture of RGB-D reconstruction are mainly degraded by the following factors:

- *The measuring error introduced by data acquirement equipment like noises, lens distortion and quantization error.*
- *The accumulated errors during camera pose estimation.*
- *The geometric error due to the sharp geometric feature over-smoothed by the moving weighted average of truncated signed distance field.*

Due to the geometric error and the camera drifting, the texture result inevitably exhibits blurring and ghosting.

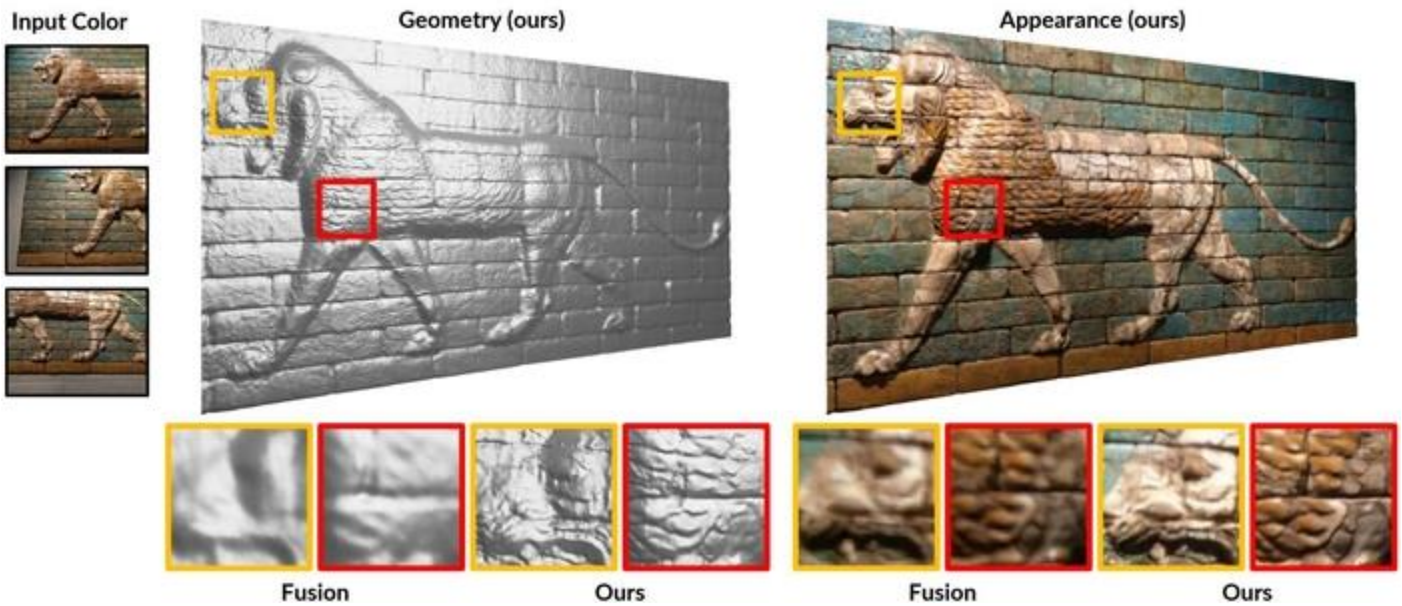


- Figure: Joint texture and geometry optimization on RGB-D scanned geometry.

(a) Without any optimization.

Related Work

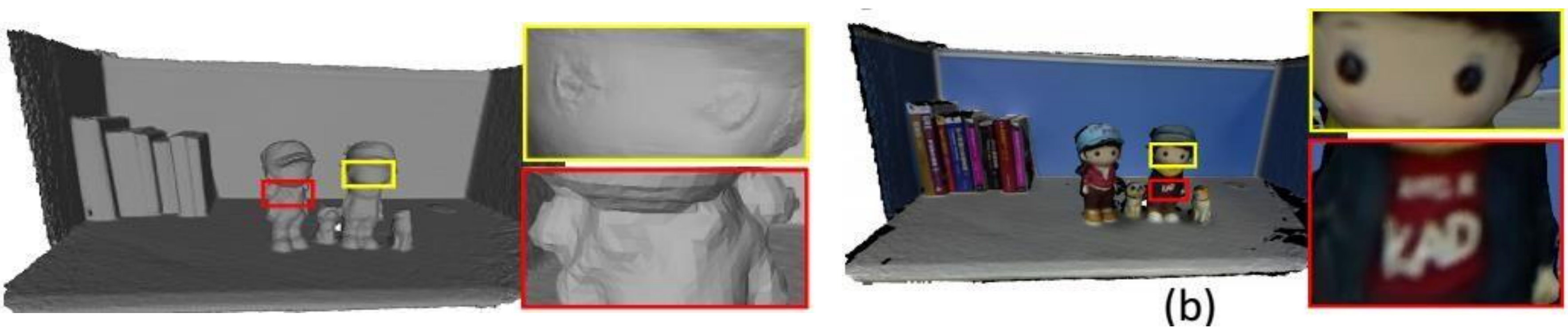
- Geometry Refinement
- Texture Optimization
- Other Joint Optimization (example: Intrinsic3D)



- Figure: Intrinsic3D: High-Quality 3D Reconstruction

Contributions

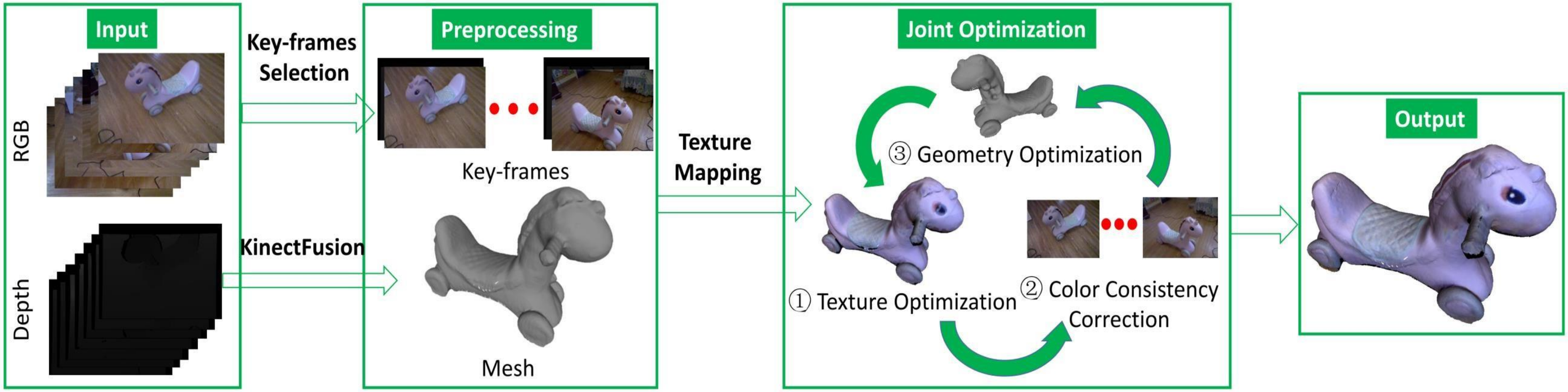
- We propose a novel method to jointly optimize the camera poses, geometric detail, texture and the color consistency between key-frames for 3D reconstruction with an RGB-D camera.
- We introduce the photometric consistency, geometric consistency and high-boost normal cues instead of SFS strategy to optimize the geometry and texture, which can effectively reduce the problem of texture-copy.
- We propose an iterative strategy for color consistency correction across key-frames, which makes the texture mapping more robust to illumination changes between views.



- Figure: Joint texture and geometry optimization on RGB-D scanned geometry.

(b) With the proposed joint optimization.

Overview



The input of the proposed method is an RGB-D sequence or stream. We utilize the depth images to reconstruct the initial 3D model and extract key-frames from the color images according to image quality. Subsequently, camera poses, geometry, texture, and color consistency between key-frames are jointly optimized in an iterative manner. The output is a 3D model with detailed geometry and high-fidelity texture.

Method

➢ **1st step: Joint optimization framework**

M_0 represent the initial reconstructed mesh model,

$\mathbf{D}$ depth image,

$\{\mathbf{v}_i\}$ vertex set of M_0

$\mathbf{C}$ color image,

M^C represents the reconstructed model M with texture color.,

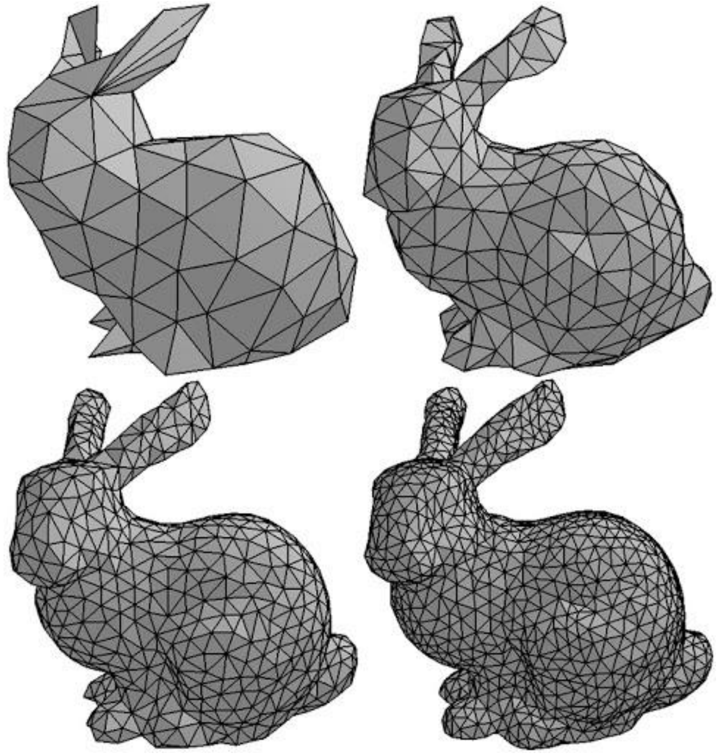
$$\mathbf{T} = \begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0} & 1 \end{bmatrix},$$ is the camera pose,

$\mathbf{v} = [x, y, z]^T$ is the vertex,

$\mathbf{u}(u, v)$ is the pixel of the image plane.,

Method

➢ **Mesh Reconstruction and Keyframes Selection**

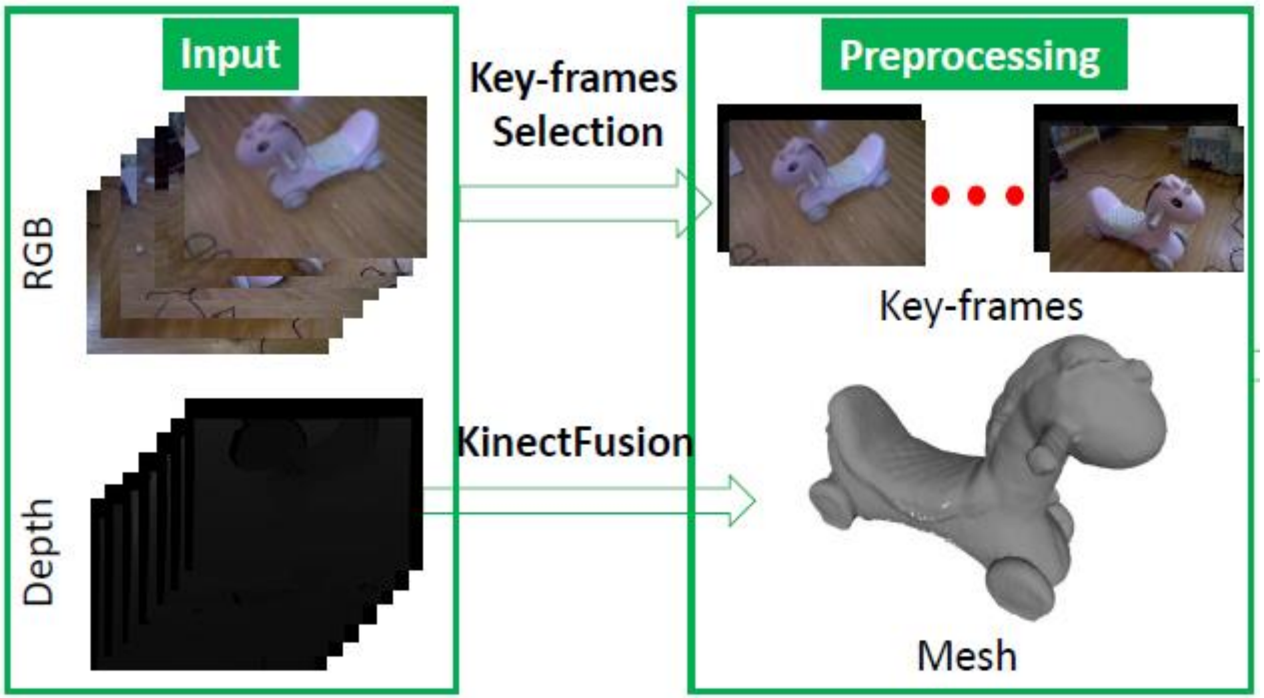


• Figure: example of 3D mesh

Method

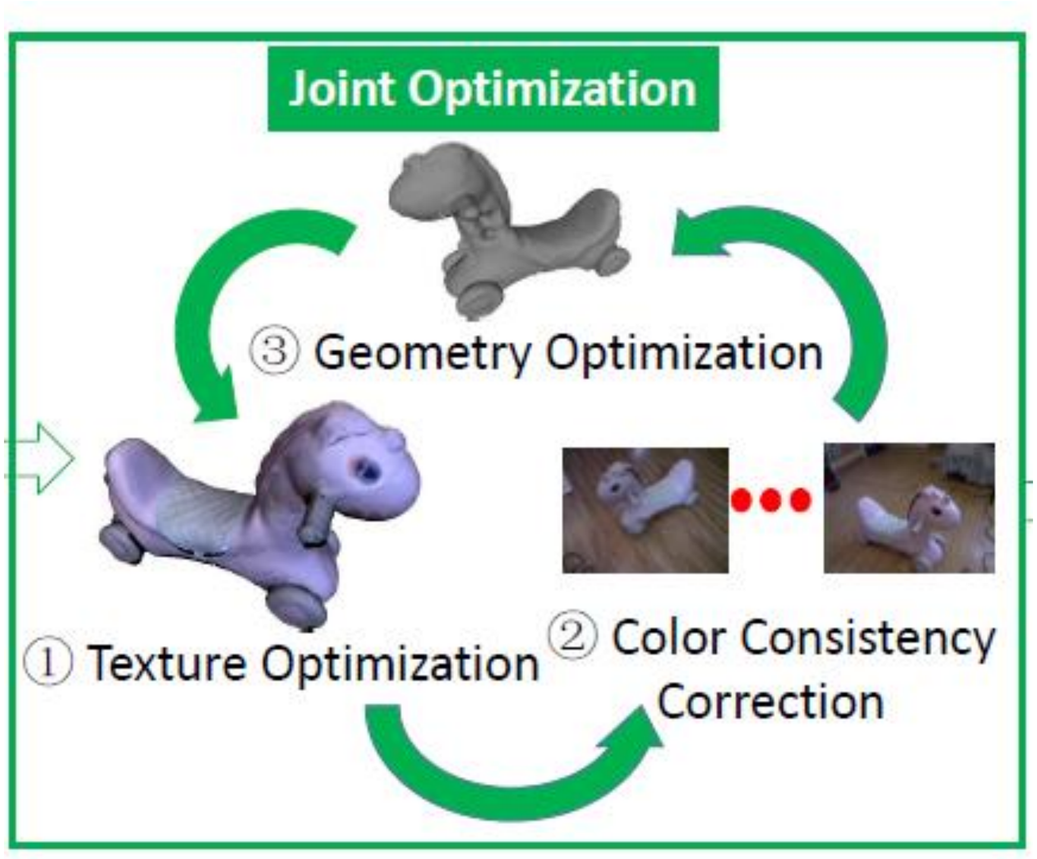
➢ **Mesh Reconstruction and Keyframes Selection**

$$C_i = \{C_i \in \Phi_{\mathrm{KF}} : \angle(\mathbf{R}_k, \mathbf{R}_i) > 30^\circ \,||\, Dist(\mathbf{t}_k, \mathbf{t}_i) > 0.2\}$$



Method

➢ **Joint Geometry and Texture Optimization**



Joint Optimization

➢ Camera Poses and Texture Optimization

We optimize the camera poses of each key-frame to ensure that the texture of the model is as consistent as possible with the texture obtained by projecting it onto all the visible key-frames. Furthermore, we not only consider color consistency but also consider the geometric consistency, which is more robust to the texture-less scene.

$$E_{\text{tex}} = \lambda_c E_c + \lambda_g E_g,$$

where

$$E_c = \sum_i^{\#\text{KF}} \sum_j^{\#\text{vert}} \left(C(\mathbf{v}_j) - I_i(\Pi(\mathbf{T}_i^{-1}\mathbf{v}_j)) \right)^2$$

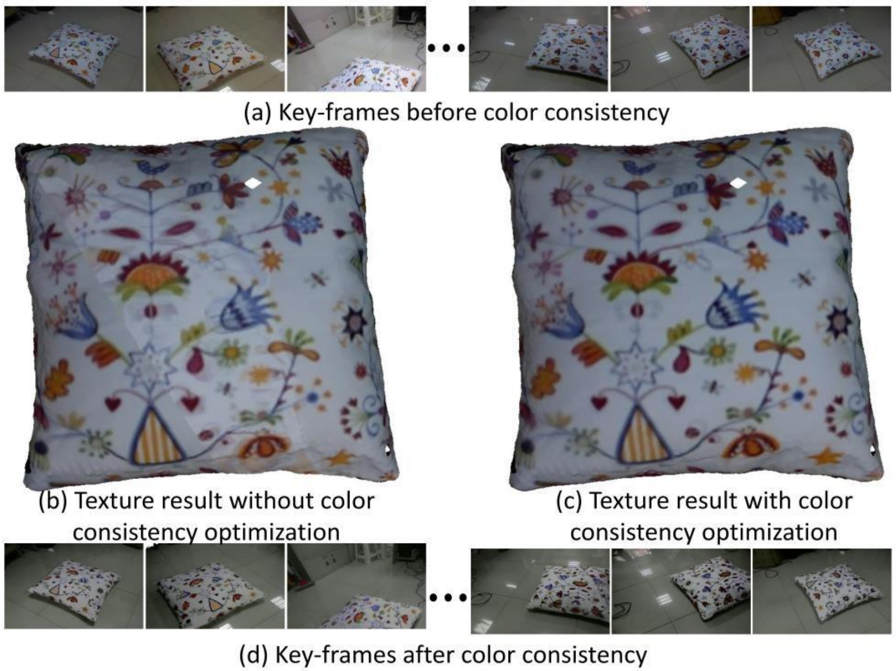
$$E_g = \sum_i^{\#\text{KF}} \sum_j^{\#\text{vert}} \left(\varphi(\mathbf{T}_i^{-1}\mathbf{v}_j) - D_i(\Pi(\mathbf{T}_i^{-1}\mathbf{v}_j)) \right)^2,$$

Joint Optimization

➢ Key-frames Color Consistency

We compute the color transfer function between the reconstruction model and key-frames to correct the color consistency between key-frames caused by illumination changes.

$$E_{color} = \sum_{i}^{\#KF} \sum_{j}^{\#vert} ||C(\mathbf{v}_j) - B_i(q_{ij})||^2 + \lambda_b \sum_{i}^{\#KF} \sum_{j}^{\#vert} (B_i^{'}(x_j) - 1)^2,$$



Joint Optimization

➢ Geometry Optimization

We take the high-boost normal as a normal consistency constraint to refine the geometry of the reconstructed model according with the photometric consistency and geometric consistency as guidance.

$$E_{\text{geo}} = E_{\text{tex}} + \lambda_H E_H + \lambda_L E_L + \lambda_R E_R,$$

The high-boost constraint term:

$$E_H = \sum_i^{\#\text{vert}} ||\mathbf{v}_i - \mathbf{v}_i^h||^2$$

The Laplacian term:

$$E_L = \sum_i^{\#\text{vert}} ||\mathbf{v}_i - \frac{1}{\sum_j \omega_{ij}} \sum_{j \in \Omega_i} \omega_{ij} \mathbf{v}_j||^2,$$

The regularization term:

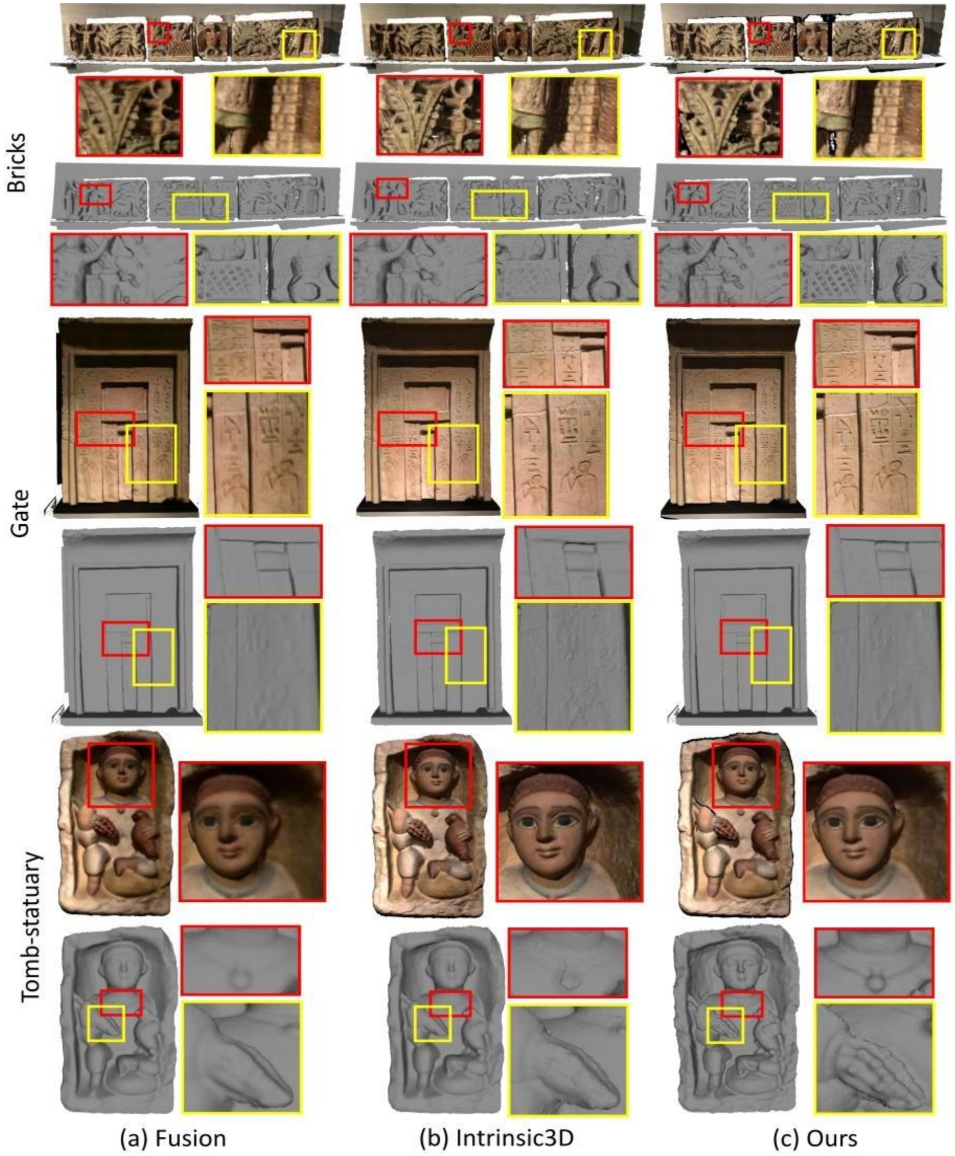
$$E_R = \sum_i^{\#\text{vert}} ||\mathbf{v}_i - \widetilde{\mathbf{v}}_i||^2$$

Minimization

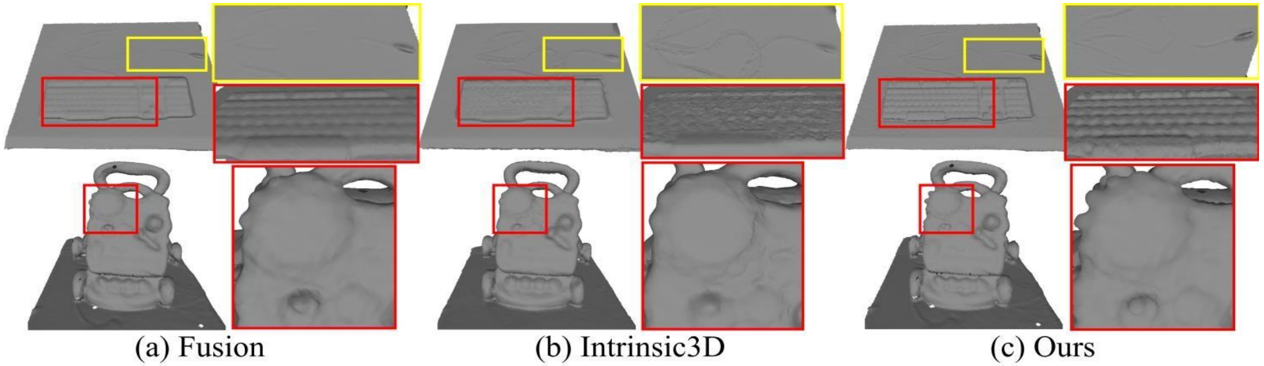
We optimize the parameters (T, B, V) in an iterative manner, where we apply external iterations to perform joint optimization.

Results

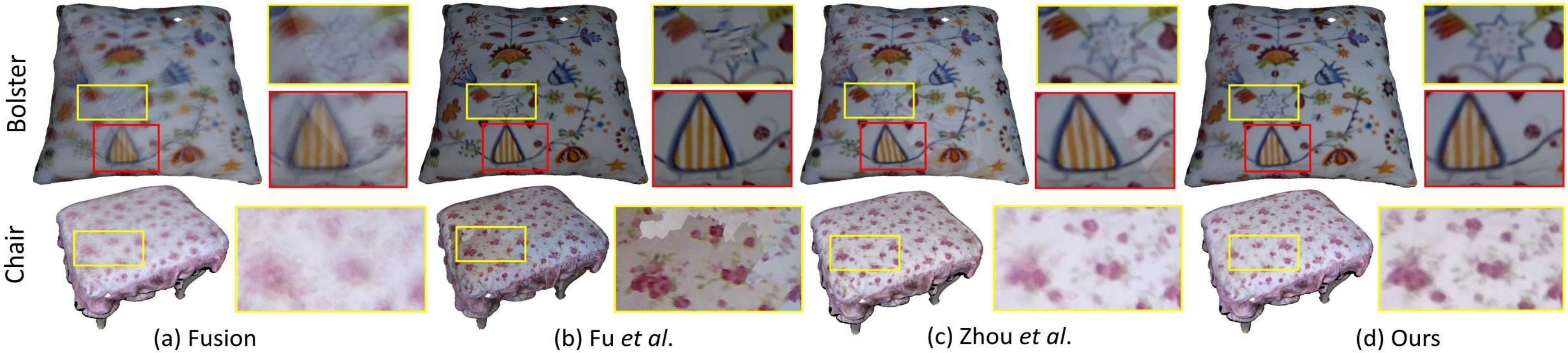
The comparison results of geometry and texture with Intrinsic3D on the datasets provided by Intrinsic3D.



Results

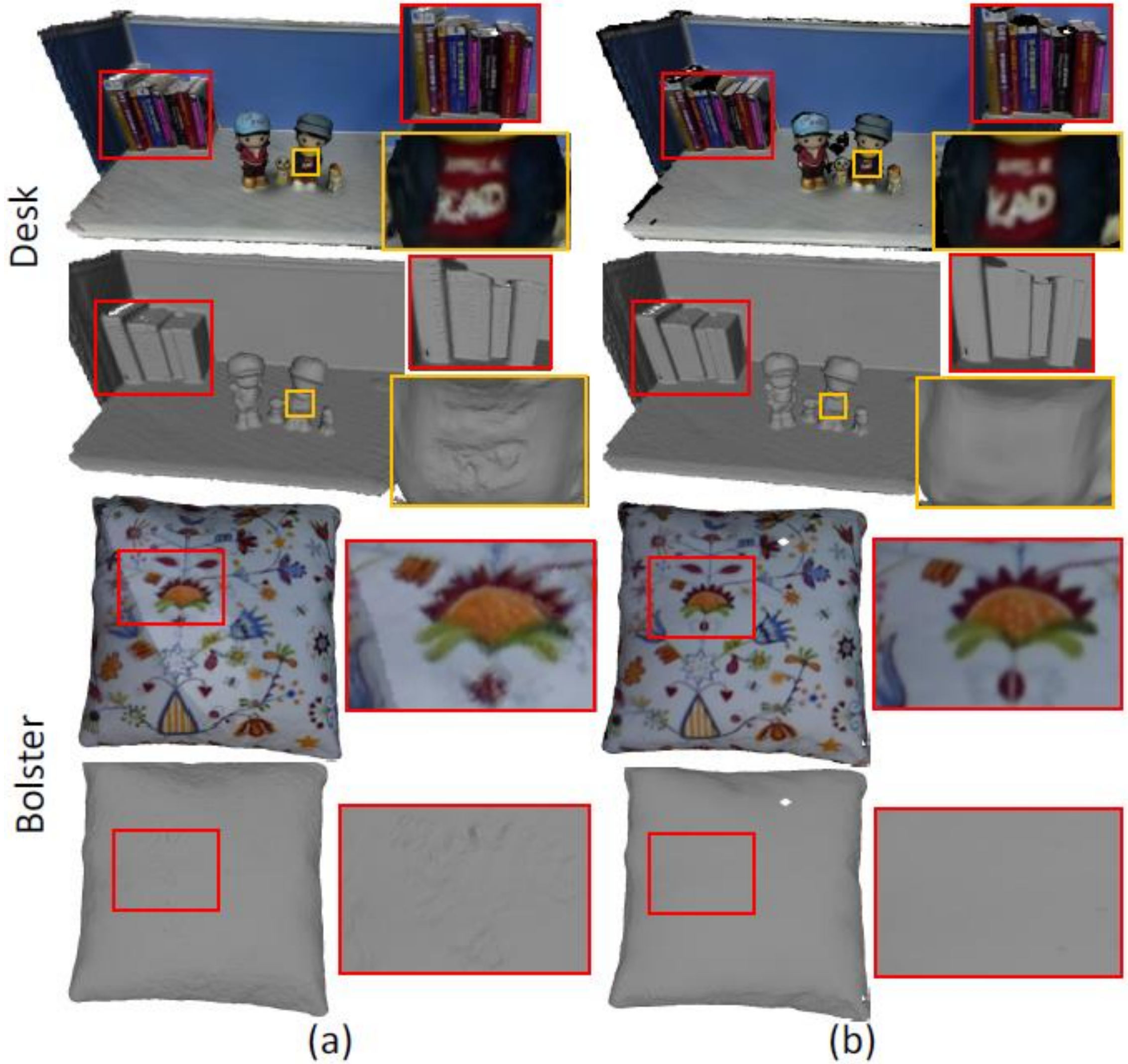


The geometry optimization comparison results.



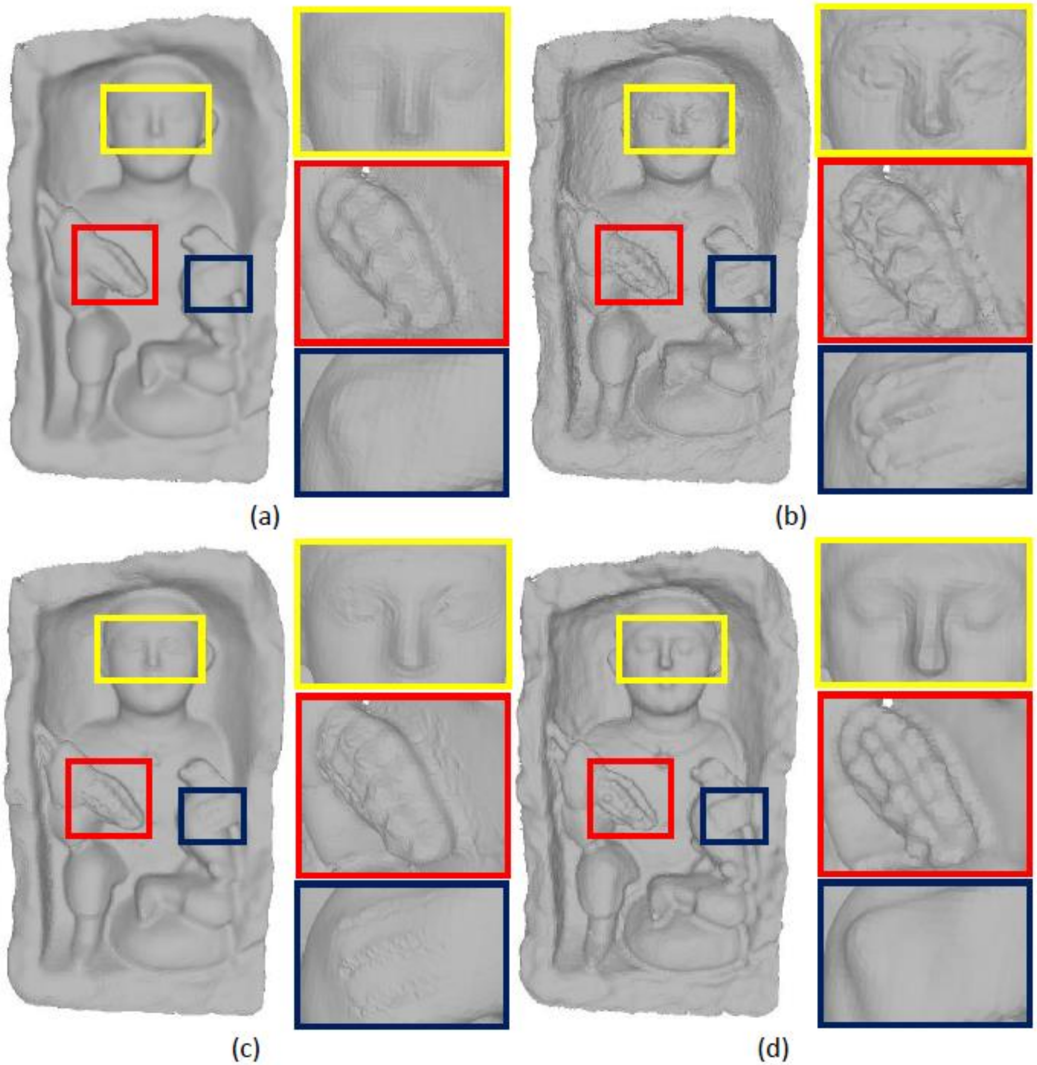
The texture optimization comparison results.

Results



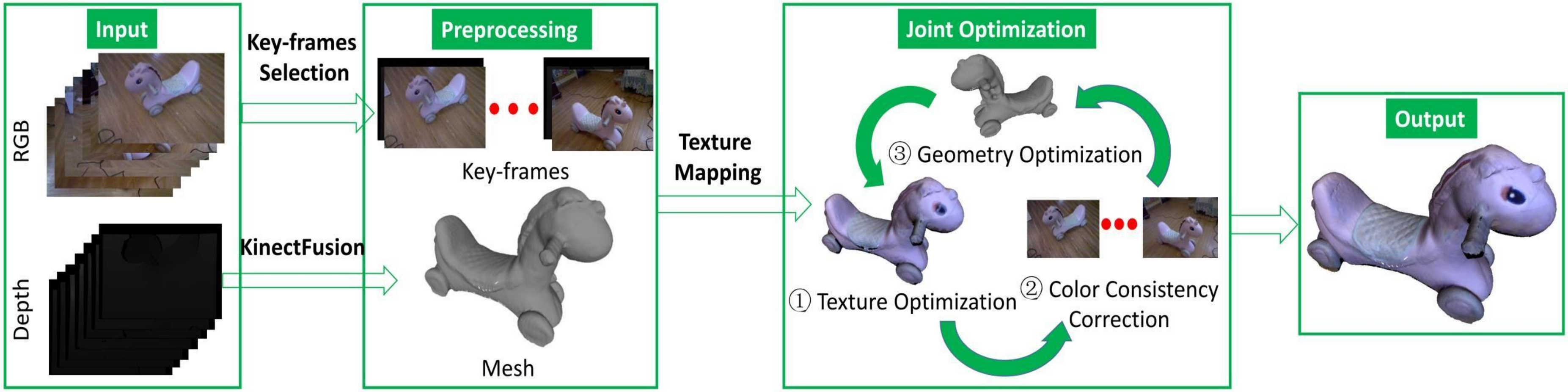
The texture-copy artifact comparison results. (a) The texture-copy artifact on the texture and geometry optimization of Intrinsic3D. (b) Our method is not affected by texture-copy.

Results



The comparison results of geometry optimization with different weights.

Conclusion



a joint optimization method to refine the texture and enhance the geometry of the 3D reconstruction by an RGB-D camera, which optimizes the camera poses, geometry and texture of the reconstructed model, and color consistency between key-frames simultaneously.