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Texture Mapping for 3D Reconstruction with RGB-D Sensor

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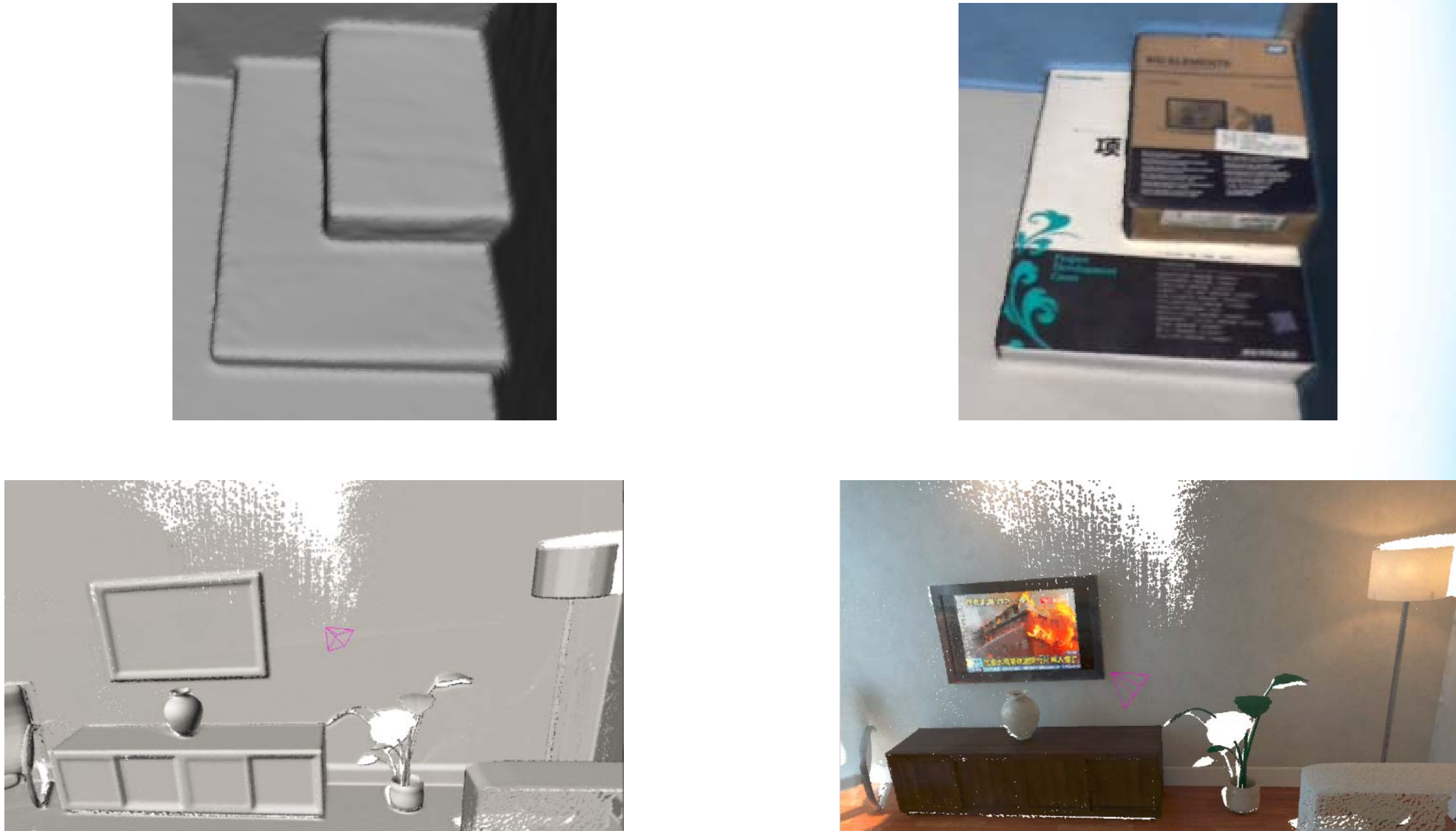
Motivation

Reconstructing high quality texture models has important significance in areas such as 3D reconstruction, cultural heritage, virtual reality and digital entertainment.



Problems

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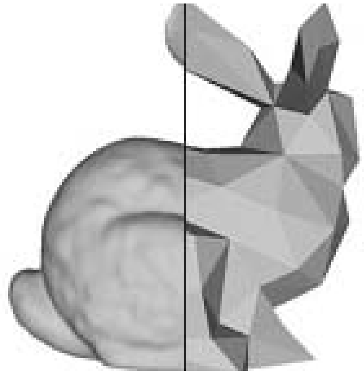
- Due to the noise of depth data, reconstructed 3D models always accompany geometric errors and distortions
- In camera trajectory estimation, the pose residual would be gradually accumulated and lead to camera drift.

- The timestamp between captured depth frame and color frame is not completely synchronized
- RGB-D sensors are usually in low resolution, and the color image is also vulnerable to light and motion conditions.
- RGB images from consumer depth cameras typically suffer from optical distortions

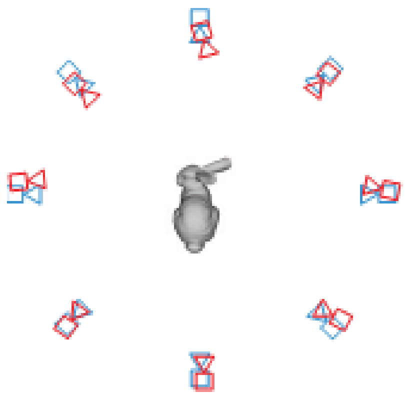
Problems

Ideally, these projected images are photometrically consistent, and thus, combining them produces a high-quality texture map.

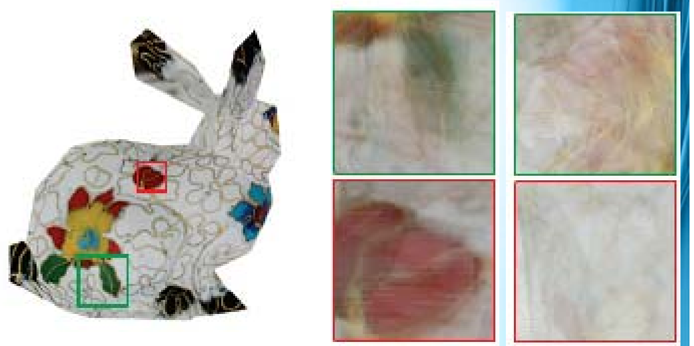
RGB Images



modle

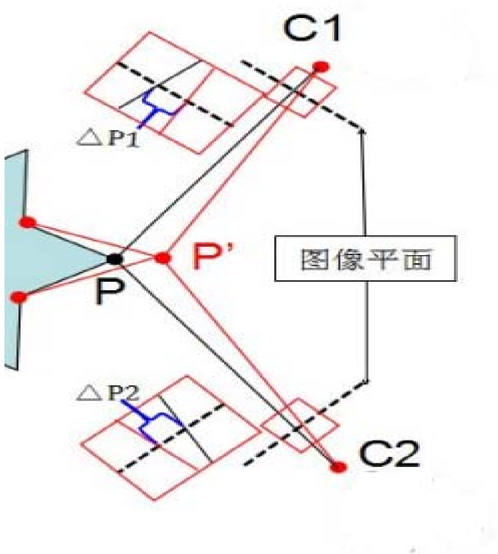


Camera poses

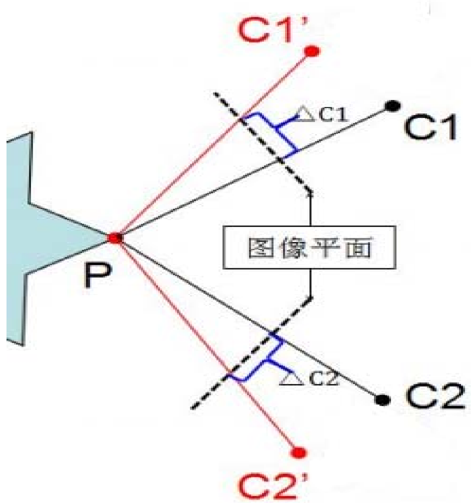


result

Problems



Geometric error



Camera pose error

Related Works

- Blending-based methods
- Projection-based methods
- Warping-based methods

Method

We propose a global-to-local correction strategy to compensate for the texture and the geometric misalignment cause by camera pose drift and geometric errors.

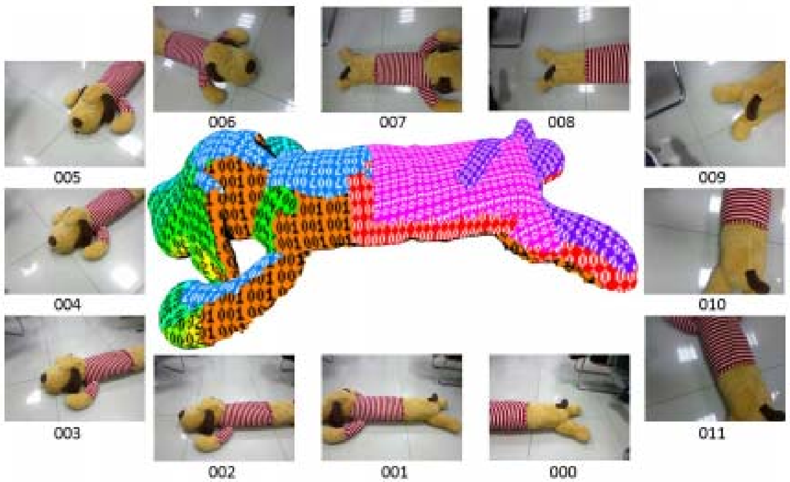
(a) Input (b) View image selection (c) Global optimization (d) Global + local optimization

Method

Preprocess: Modify the sparse-sequence fusion method [4] to reconstruct 3D and select texture candidate images by weighting the elements of image clarity (E_{cla}), jitter (E_{jit}), motion velocity (E_{vel}) and viewport overlay (E_{dif}).

$$E = E_{jit} + E_{dif} + E_{vel} + E_{cla} + E_{sel}$$

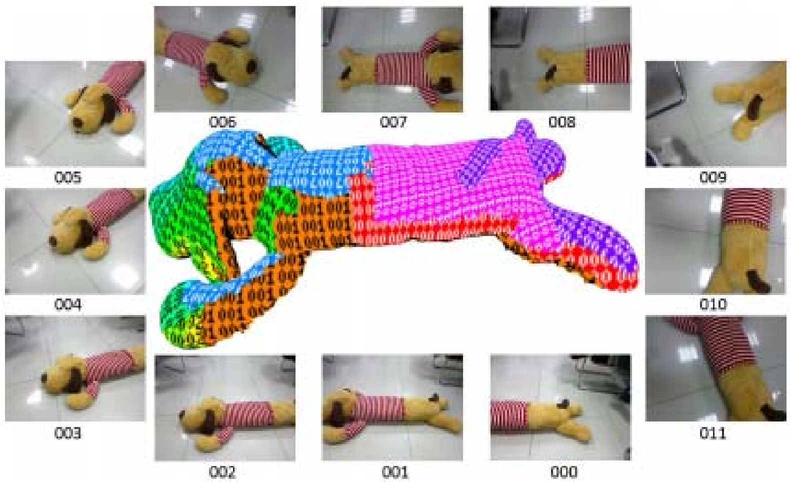
Texture Image Selection: To construct high fidelity texture, we select an optimal texture image for each face of the model to avoid the blurring caused by multi-image blending.



Method

- **Global Optimization:** Because both camera pose T and reconstructed M are not absolutely accurate, adjacent faces with different labels usually can not be completely stitched. We first adjust the camera pose of each texture chart based on the color consistency and geometric consistency between relevant charts.

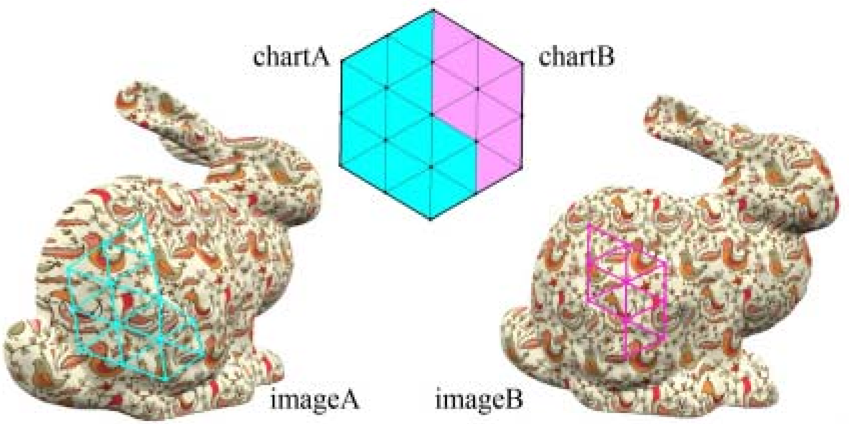
$$E(T)=\sum_{i}^{chN}\sum_{j\in G_i}\sum_{k\in ch_i}^{N}\left(I_i(\Pi(T_i v_k))-I_j(\Pi(T_j v_k))\right)^2+\lambda\sum_{i}^{chN}\sum_{k\in ch_i}^{N}\left(\varphi(T_i v_k)-D(\Pi(T_i v_k))\right)^2$$

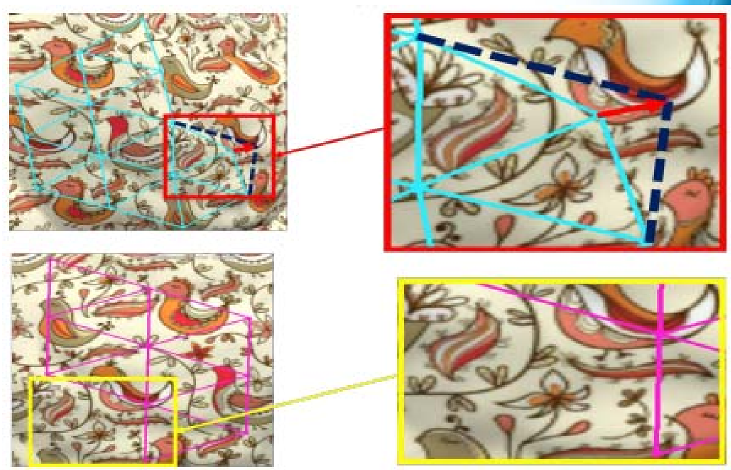


Method

- **Local Optimization:** The global optimization can only correct the camera drift of each chart. But the ubiquity of geometry errors makes the only global optimization is insufficient for high fidelity texture mapping. we import an a local adjustment to refine texture coordinates of each vertex on the boundary of chart and make seamlessly stitched textures.

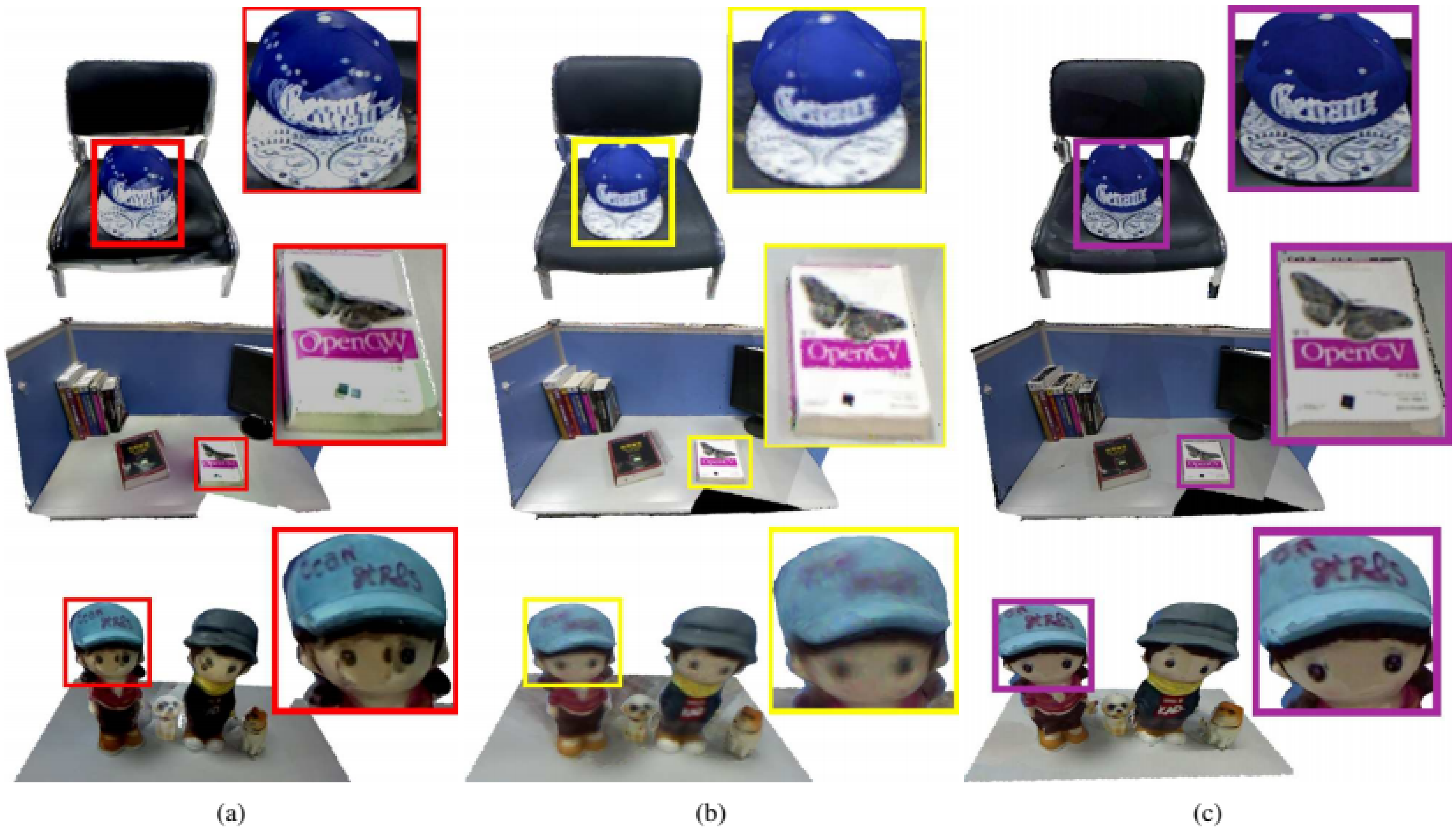
$$E(T_{ij}) = \sum_{i}^{chN}\sum_{j}^{N}\sum_{k\in A_i}\left(I_i\left(\Pi\left(T_{ij}T_i v_j\right)\right) - I_k\left(\Pi\left(T_{kj}T_k v_j\right)\right)\right)^2 + \lambda\sum_{i}^{chN}\sum_{j}^{N}\left(T_{ij}^{T}T_{ij} - I\right)$$



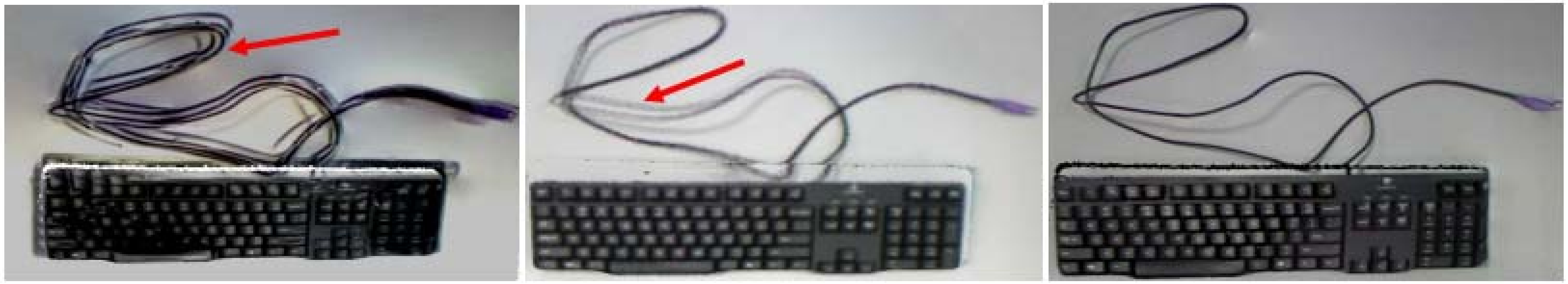


Results

The comparisons between the state-of-the-art approaches Waechter et al. [1] (left) Zhou et al. [2] (middle) and ours (right) on several datasets acquired by Kinect。



Results



(a) (b) (c)

(a) (b) (c) (d)

Results

The performance statistics of Waechter et al. [23], Zhou et al. [30]and our algorithm.

	scene information			running time (s)					
model	points	faces	key frames	T_s	T_g	T_l	T_t	[23]	[30]
toy	40705	79682	14	1.087	16.591	4.446	27.608	147.068	341.755
book	178584	352510	16	2.262	84.792	57.053	157.014	486.649	902.207
hat	70623	137767	10	2.475	29.193	13.263	59.949	214.774	1002.190
keyboard	68238	134475	13	4.223	26.478	7.594	47.637	321.973	1513.080

Limitations

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- The texture may be stretched and shrunk on the boundary of charts
- When geometric error is large, the correction would still generate some local texture distortions to final mapping results.

Reference

1. Q. Y. Zhou and V. Koltun. Color map optimization for 3d reconstruction with consumer depth cameras. Acm Transactions on Graphics, 33(4):1–10, 2014.

2. M. Waechter, N. Moehrle, and M. Goesele. Let there be color! large-scale texturing of 3d reconstructions. In European Conference on Computer Vision, pages 836–850, 2014.

3. S. Bi, N. K. Kalantari, and R. Ramamoorthi. Patch-based optimization for image-based texture mapping. *ACM Transactions on Graphics (Proceedings of SIGGRAPH 2017)*, 36(4), 2017.

4. L. Yang, Q. Yan, Y. Fu, and C. Xiao. Surface reconstruction via fusing sparse-sequence of depth images. In TVCG, 2017.

Q&A

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