

A NOVEL KINECT V2 REGISTRATION METHOD FOR LARGE-DISPLACEMENT ENVIRONMENTS USING CAMERA AND SCENE CONSTRAINTS

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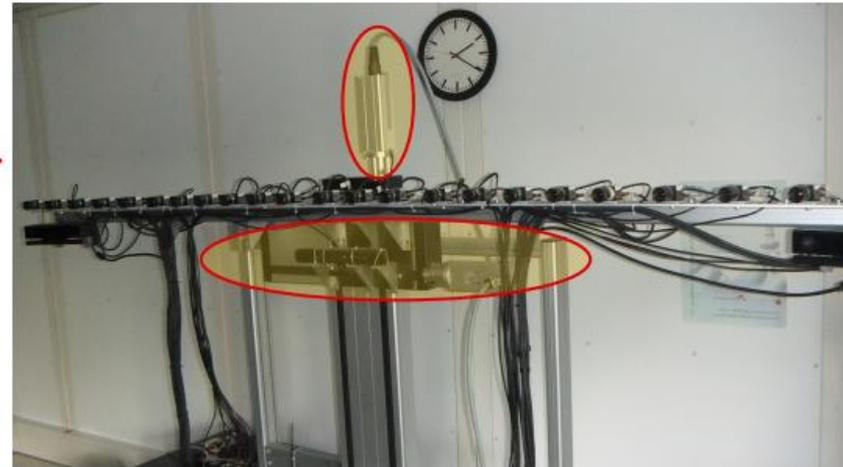
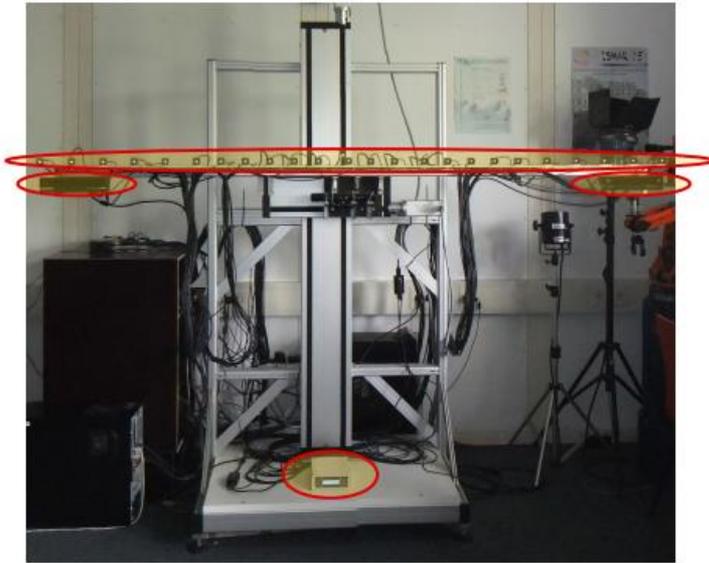
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Outline

- Motivation**
- Related Work
- Proposed Method
- Experiments
- Conclusion

Motivation



❑ Multi-camera light field rig

- ❑ 24× IDS USB 3 uEye CP **RGB cameras** at 2 hosts (12 per host)
- ❑ 2× Microsoft **Kinect V2** RGB-D cameras at 1 host
- ❑ 1× Isel iMC-S8 **microstep controller** for 2 linear axes
- ❑ 1× **Hardware trigger** for synchronized uEye camera capture

Motivation

- ❑ Kinect V2 cameras
 - ❑ **Large displacement:** 2.4 meters
- ❑ ToF sensor in a Kinect V2 camera
 - ❑ Resolution: **512 × 424** pixels
 - ❑ FOV: **71° × 60°**
- ❑ RGB sensor in a Kinect V2 camera
 - ❑ Resolution: **1,920 × 1,080** pixels
 - ❑ FOV: **84° × 54°**
- ❑ The traditional checkerboard-based calibration method [1] is prone to fail if the checkerboard is not huge enough for being captured.

[1] Zhang, A flexible new technique for camera calibration, TPAMI 2000, vol. 22, no. 11, pp. 1330-1334.

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Related Work

- ❑ For **non-large-displacement** environment
 - ❑ BAICP, ICPR 2014 [2]
 - ❑ 3D correspondence-based method, ICMEW 2015 [3]
 - ❑ An optical tracking system, 3DUI 2015 [4]
 - ❑ OpenPTrack, RAS 2016 [5]
 - ❑ Coarse-to-fine framework
 - ❑ 3DV 2015 [6]
 - ❑ Coarse estimation: Marker (2D)
 - ❑ Estimation refinement: Iterative Closest Point (ICP)
 - ❑ SCP 2017 [7]
 - ❑ Coarse estimation: Wand (1D)
 - ❑ Estimation refinement: R-Nearest Neighbor (RNN)

Related Work

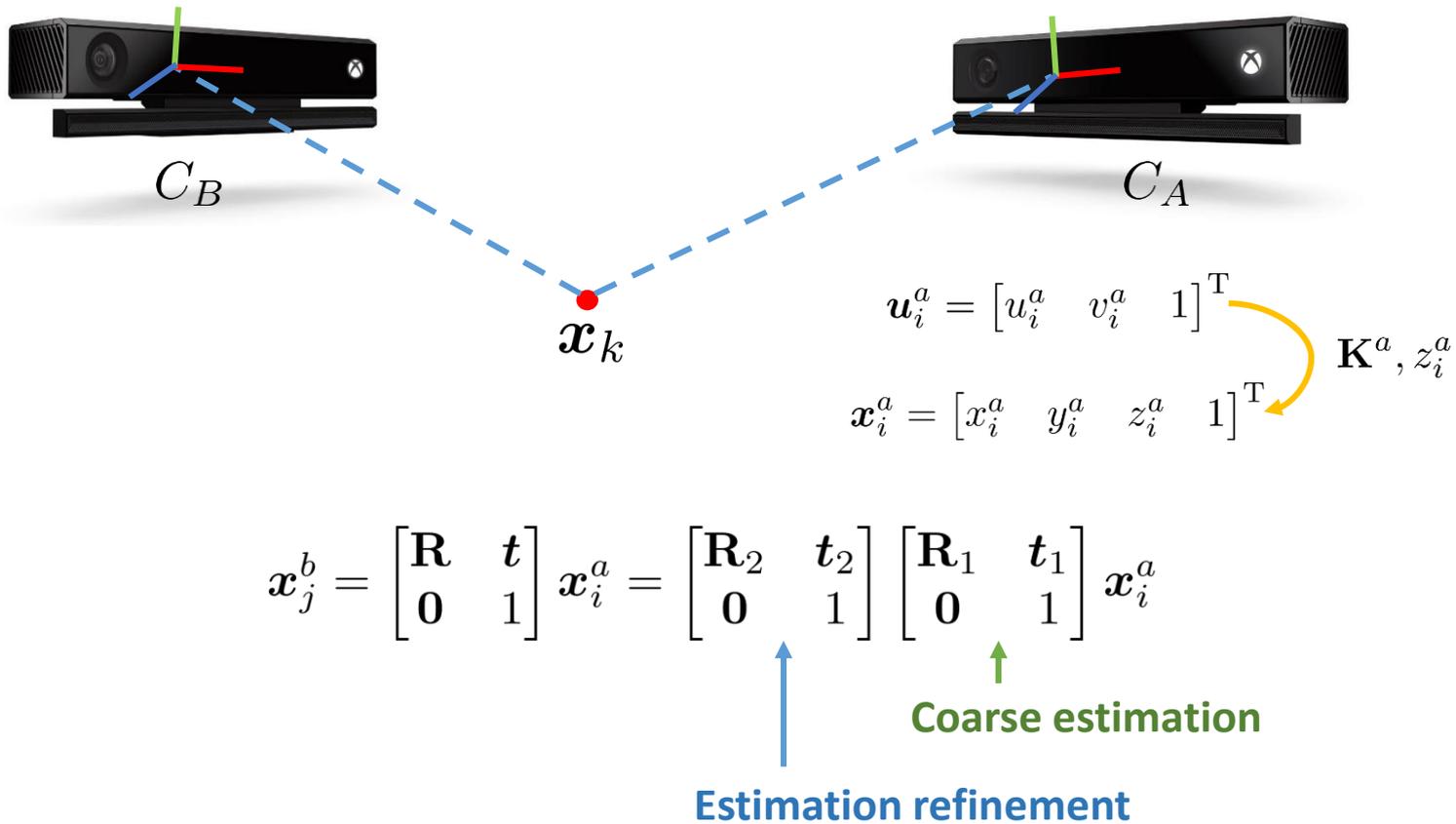
- [2] Afzal et al., RGB-D multi-view system calibration for full 3D scene reconstruction, ICPR 2014, pp. 2459-2464.
- [3] Palasek et al., A flexible calibration method of multiple Kinects for 3D human reconstruction, ICMEW 2015, pp. 1-4.
- [4] Beck and Froehlich, Volumetric calibration and registration of multiple RGBD-sensors into a joint coordinate system, 3DUI 2015, pp. 89-96.
- [5] Munaro et al., Openptrack: Open source multi-camera calibration and people tracking for RGB-D camera networks, RAS 2016, vol. 75, pp. 525–538.
- [6] Kowalski et al., LiveScan3D: A fast and inexpensive 3D data acquisition system for multiple Kinect V2 sensors, 3DV 2015, pp. 318–325.
- [7] Cordova-Esparza et al., A multiple camera calibration and point cloud fusion tool for Kinect V2, Science of Computer Programming (SCP 2017), vol. 143, pp. 1-8.

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Proposed Method

□ Preliminary



Proposed Method

□ Stage 1: Coarse estimation

□ With calibration objects (**baseline approach**)

$$\min_{\mathbf{R}_1, t_1} \sum_{i=1}^n \| \mathbf{u}_i^b - \hat{\mathbf{u}}(\mathbf{x}_i^a, \mathbf{K}^b, \mathbf{R}_1, t_1) \|^2$$

where $\hat{\mathbf{u}}(\mathbf{x}, \mathbf{K}, \mathbf{R}, t) = \text{proj}(\mathbf{K} [\mathbf{R} \quad t] \mathbf{x})$

A standard Perspective- n -Point (PnP) problem

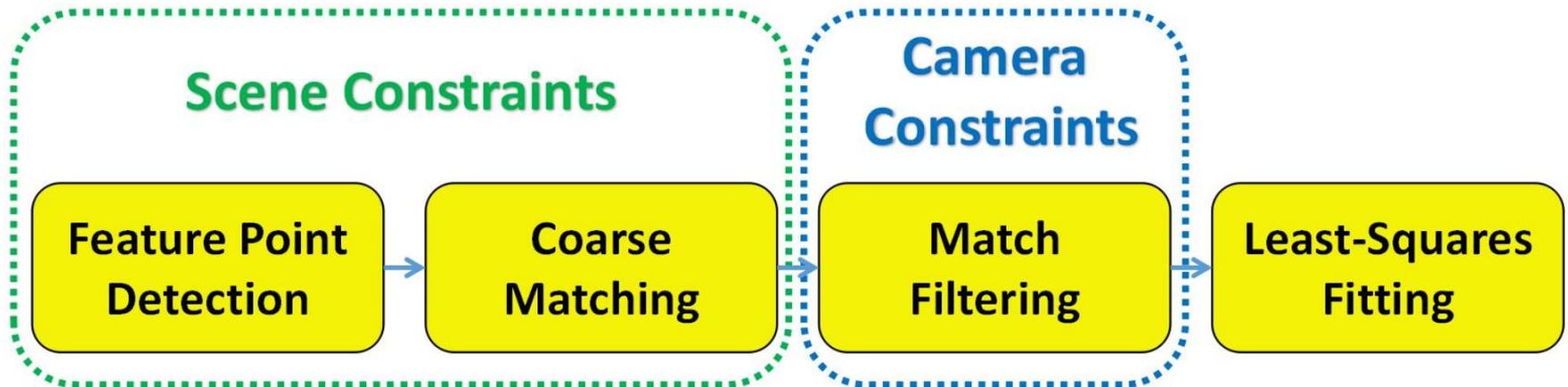
- Levenberg-Marquardt optimization algorithm;
- EPnP [8], RPnP [9], etc.

[8] Lepetit et al., EpnP: An accurate $O(n)$ solution to the PnP problem, IJCV 2009, vol. 81, no. 2, pp. 155-166.

[9] Li et al., A robust $O(n)$ solution to the Perspective- n -Point problem, TPAMI 2012, vol. 34, no. 7, pp. 1444-1450.

Proposed Method

- Stage 1: Coarse estimation
 - With camera and scene constraints



SURF

k -Nearest-Neighbors (KNN)
Ratio test

RANSAC

$$\mathbf{u}_i^b \sim \mathbf{H}\mathbf{u}_i^a$$

$$(\mathbf{u}_i^b)^T \mathbf{F}\mathbf{u}_i^a = 0$$

$$\min_{\mathbf{R}_1, t_1} \sum_{i=1}^n \left\| \mathbf{x}_i^b - \begin{bmatrix} \mathbf{R}_1 & t_1 \\ \mathbf{0} & 1 \end{bmatrix} \mathbf{x}_i^a \right\|^2$$

Proposed Method

□ Stage 2: Estimation refinement

input : P_A - Point cloud of C_A after the rigid transformation of the coarse estimation stage;
 P_B - Point cloud of C_B ;
 N - Number of point cloud registration iterations;
 $\mathbf{R}^a, \mathbf{R}^b$ - 3×3 identity matrices;
 $\mathbf{t}^a, \mathbf{t}^b$ - 3×1 zero vectors.
output: $\mathbf{R}^a, \mathbf{R}^b, \mathbf{t}^a, \mathbf{t}^b$.

```

for  $n \leftarrow 1$  to  $N$  do
     $\mathbf{R}, \mathbf{t} \leftarrow \text{ICP}(P_A, P_B)$ ;
    for each point  $\mathbf{x}_i^a$  in  $P_A$  do
         $\mathbf{x}_i^a \leftarrow \begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0} & 1 \end{bmatrix} \mathbf{x}_i^a$ ;
    end
     $\mathbf{R}^a \leftarrow \mathbf{R}\mathbf{R}^a$ ;
     $\mathbf{t}^a \leftarrow \mathbf{R}\mathbf{t}^a + \mathbf{t}$ ;
     $\mathbf{R}, \mathbf{t} \leftarrow \text{ICP}(P_B, P_A)$ ;
    for each point  $\mathbf{x}_i^b$  in  $P_B$  do
         $\mathbf{x}_i^b \leftarrow \begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0} & 1 \end{bmatrix} \mathbf{x}_i^b$ ;
    end
     $\mathbf{R}^b \leftarrow \mathbf{R}\mathbf{R}^b$ ;
     $\mathbf{t}^b \leftarrow \mathbf{R}\mathbf{t}^b + \mathbf{t}$ ;
end
    
```

Fix P_B
Move P_A

Fix P_A
Move P_B

$$\mathbf{x}_k = \begin{bmatrix} \mathbf{R}^a & \mathbf{t}^a \\ \mathbf{0} & 1 \end{bmatrix} \mathbf{x}_i^a = \begin{bmatrix} \mathbf{R}^b & \mathbf{t}^b \\ \mathbf{0} & 1 \end{bmatrix} \mathbf{x}_j^b$$



$$\mathbf{R}_2 = (\mathbf{R}^b)^T \mathbf{R}^a$$

$$\mathbf{t}_2 = (\mathbf{R}^b)^T (\mathbf{t}^a - \mathbf{t}^b)$$

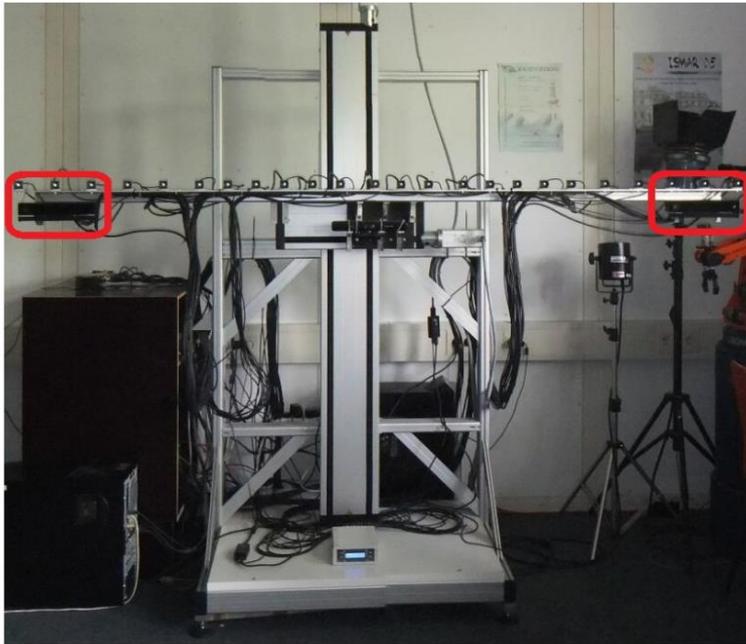
Algorithm 1: Point cloud registration

Outline

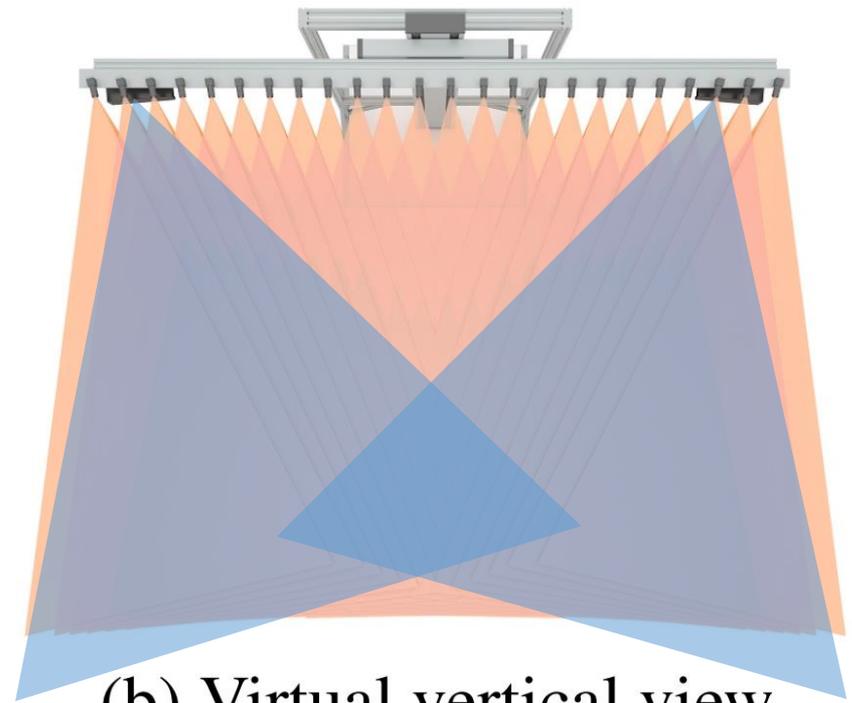
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Experiments

☐ Capture device



(a) Frontal view



(b) Virtual vertical view

Experiments

Registered color images

512

424

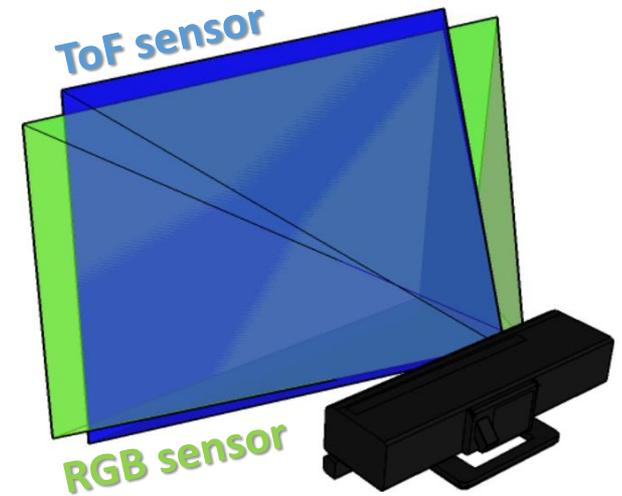


(a) C_A view of the checkerboard (b) C_B view of the checkerboard



(c) C_A view of the scene

(d) C_B view of the scene



Experiments

□ Experimental Settings

□ Checkerboard-captured data

- In front of the rig at a distance of **2.8** m;
- **28** (4×7) inner corners;
- Square size: **124** × **124** mm.

□ Scene-captured data

- Captured room size: **5.5** × **3.0** × **7.8** m (w × h × d)

□ Evaluation metric

- Root-Mean-Square Error (**RMSE**)

$$\sqrt{\frac{1}{n} \sum_{i=1}^n \left\| \mathbf{x}_i^b - \begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0} & 1 \end{bmatrix} \mathbf{x}_i^a \right\|^2}$$

□ Others

- *libfreenect2* -> **registered** color and depth image

Experiments

Quantitative evaluation

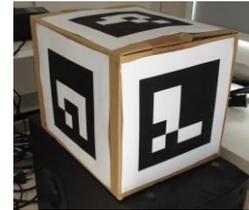
Table I. RMSE of the coarse-to-fine registration methods.

Coarse Estimation	RMSE (mm)	Estimation Refinement	RMSE (mm)
Checkerboard-based	78.33	ICP-based point cloud registration	84.11
Homography matrix-based	302.05	ICP-based point cloud registration	44.82
Fundamental matrix-based	295.58	ICP-based point cloud registration	34.34

- In the coarse estimation stage,
 - checkerboard-based method achieves much more precise results than the homography and fundamental matrices-based methods.
- In the estimation refinement phase,
 - the precision of the checkerboard-based method **decreases a little bit**;
 - the precision of coarse estimation methods using camera and scene constraints **improves dramatically**.

Experiments

☐ Qualitative evaluation



(a) Checkerboard-based coarse estimation with estimation refinement

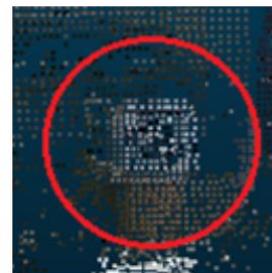


(b)

Checkerboard-based coarse-to-fine method



(c) Fundamental matrix-based coarse estimation with estimation refinement



(d)

Fundamental matrix-based coarse-to-fine method

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Conclusion

- ❑ Camera and scene constraints are exploited inside a **coarse-to-fine framework** to solve the Kinect V2 registration problem in the **large-displacement** environment;
- ❑ The **fundamental matrix-based** coarse-to-fine registration method outperforms the checkerboard-based coarse-to-fine registration method on a multi-camera rig with a large displacement between two Kinect V2 sensors.



Thank you!