Better Prior Knowledge Improves Human-Pose-Based Extrinsic Camera Calibration

Olivier Moliner [1,2]   Sangxia Huang [2]   Kalle Åström [1]

[1]Lund University, Sweden   [2]Sony R&D Center Lund, Sweden

LUND UNIVERSITY

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Motivation

- **Accurate extrinsic calibration of wide baseline multi-camera systems** with classical Structure-from-Motion methods requires special calibration equipment and trained operators.

- This is costly and time-consuming, and limits the ease of adoption of multi-camera 3D scene analysis technologies.

Prior work

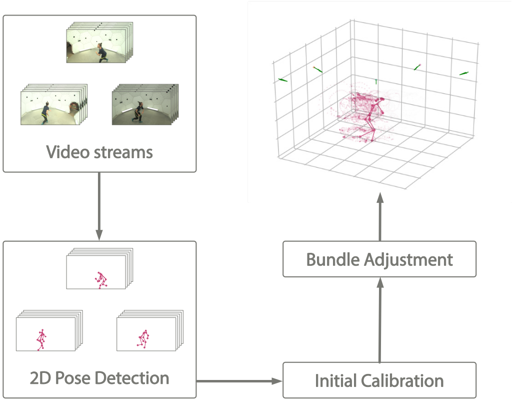
- Use human pose estimation models to establish point correspondences, thus removing the need for any special equipment.
- **Challenge:** human pose estimation algorithms produce much less accurate feature points compared to patch-based methods.

Our Contribution

- **A robust reprojection loss** more suitable for camera calibration with human poses.
- We introduce a **3D-human-pose likelihood model** to the objective function of bundle adjustment.

Method

- 2d human pose estimation.
- Initial calibration
- Bundle adjustment



Objective function

$$E = E_{rep} + E_{motion} + E_{limb} + E_{KCS}$$

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E_{rep} **Robust Reprojection Error**

$$E_{rep} = \frac{1}{\sum_{i,j,t} w_{ijt}} \sum_{i,j,t} w_{ijt} L(u_{ijt}, \pi_{\mathbf{i}}(\mathbf{U_{jt}}))\ ,$$

where $L(\cdot, \cdot)$ is the Huber loss function, and the weights w_{ijt} depend on the joint detection scores and the distances between the joints and the cameras.

Objective function

$$E = E_{rep} + E_{motion} + E_{limb} + E_{KCS}$$

E_{motion} **Motion prior**

- the l_2-norm of the fourth-order derivative of the joint positions
- encourages smooth joint trajectories while accounting for complex human motion

Objective function

$$E = E_{rep} + E_{motion} + E_{limb} + E_{KCS}$$

E_{limb} **Constant Limb Length Constraint**

- enforces the reconstructed limb lengths to stay constant throughout the whole sequence.

Objective function

$$E = E_{rep} + E_{motion} + E_{limb} + E_{KCS}$$

E_{KCS} **Body Pose Prior**

- average likelihood of the 3D human poses, given by a PCA model fitted on the Human 3.6M dataset.
- encourages the reconstruction of plausible human poses

Datasets

- Human 3.6M
- CMU Panoptic
- Soccer Juggling and Sword Swing sequences

Comparison to previous work

	Puwein et al.[1]		Proposed Solution	
	Pos.	Ang.	Pos.	Ang.
Soccer	5.0	1.0	1.7	0.4
Sword	5.8	1.0	0.9	0.4

[1] Jens Puwein et al. "Joint Camera Pose Estimation and 3D Human Pose Estimation in a Multi-camera Setup". In: *Computer Vision – ACCV 2014*. Springer International Publishing, Nov. 2014, pp. 473–487.

Ablation study

ID	Reproj.	Motion	KCS	Limb	H36M `Walking` Pos.	H36M `Walking` Ang.	H36M `WalkTogether` Pos.	H36M `WalkTogether` Ang.	Dance Pos.	Dance Ang.	Soccer Pos.	Soccer Ang.	Sword Pos.	Sword Ang.
0	Initial calibration				4.41 ± 2.66	0.54 ± 0.20	5.81 ± 3.25	0.67 ± 0.34	5.56 ± 1.21	0.78 ± 0.24	13.84 ± 3.86	3.52 ± 1.20	19.86 ± 2.48	4.21 ± 0.45
1					4.87 ± 1.50	0.60 ± 0.15	4.11 ± 1.52	0.53 ± 0.20	3.89 ± 0.36	0.54 ± 0.03	3.47 ± 0.05	0.60 ± 0.01	2.46 ± 0.12	1.20 ± 0.00
2	✓				2.04 ± 0.77	0.31 ± 0.09	2.88 ± 2.08	0.36 ± 0.22	4.17 ± 0.51	0.49 ± 0.16	1.87 ± 0.09	0.47 ± 0.01	1.10 ± 0.12	0.38 ± 0.02
3	✓	✓			2.04 ± 0.77	0.31 ± 0.09	2.84 ± 2.00	0.35 ± 0.21	4.05 ± 0.44	0.46 ± 0.14	2.04 ± 0.14	0.49 ± 0.02	1.09 ± 0.11	0.38 ± 0.02
4	✓		✓		1.88 ± 0.71	0.29 ± 0.09	2.60 ± 1.85	0.33 ± 0.19	4.04 ± 0.44	0.47 ± 0.15	2.10 ± 0.11	0.49 ± 0.02	1.00 ± 0.08	0.37 ± 0.02
5	✓			✓	2.00 ± 0.76	0.31 ± 0.09	2.85 ± 2.32	0.37 ± 0.25	4.09 ± 0.45	0.46 ± 0.14	1.44 ± 0.09	0.43 ± 0.02	0.89 ± 0.09	0.38 ± 0.01
6	✓	✓		✓	1.96 ± 0.74	0.30 ± 0.09	2.81 ± 2.25	0.36 ± 0.24	4.01 ± 0.40	0.45 ± 0.13	1.80 ± 0.12	0.48 ± 0.02	0.89 ± 0.08	0.38 ± 0.01
7		✓	✓	✓	4.36 ± 1.07	0.53 ± 0.11	4.21 ± 1.62	0.52 ± 0.20	4.13 ± 0.53	0.51 ± 0.11	2.16 ± 0.24	0.70 ± 0.02	2.44 ± 0.12	1.00 ± 0.01
8	✓	✓	✓	✓	1.89 ± 0.72	0.29 ± 0.09	2.66 ± 2.08	0.34 ± 0.22	4.02 ± 0.42	0.45 ± 0.14	1.66 ± 0.12	0.44 ± 0.02	0.86 ± 0.05	0.38 ± 0.01
9	Plain vanilla BA with $\theta_{ba} = 0.7$				2.68 ± 0.79	0.33 ± 0.09	2.81 ± 1.17	0.35 ± 0.13	4.16 ± 0.65	0.46 ± 0.09	2.62 ± 0.09	0.69 ± 0.01	1.32 ± 0.02	0.91 ± 0.00
10	Our solution with $\theta_{ba} = 0.7$				2.00 ± 0.76	0.31 ± 0.09	2.69 ± 2.09	0.35 ± 0.22	4.03 ± 0.46	0.46 ± 0.15	1.50 ± 0.10	0.42 ± 0.02	0.96 ± 0.07	0.39 ± 0.02

Conclusion

- We introduced several ideas in this paper and achieved improved accuracy for extrinsic camera calibration using human body joints.
- We showed that robust loss functions and relevant prior models are effective in handling errors in human body joint detection.