Camera Calibration Through Camera Projection Loss

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icassp 2022 Singapore
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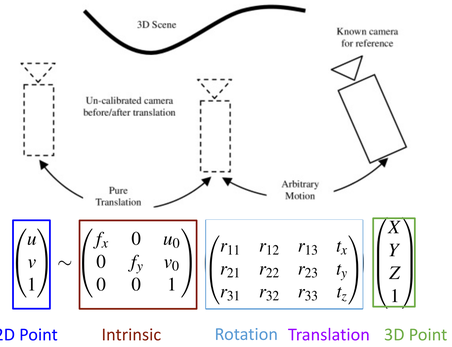
1. Motivation

Camera Calibration



$$\begin{pmatrix} u \\ v \\ 1 \end{pmatrix} \sim \begin{pmatrix} f_x & 0 & u_0 \\ 0 & f_y & v_0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \end{pmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix}$$

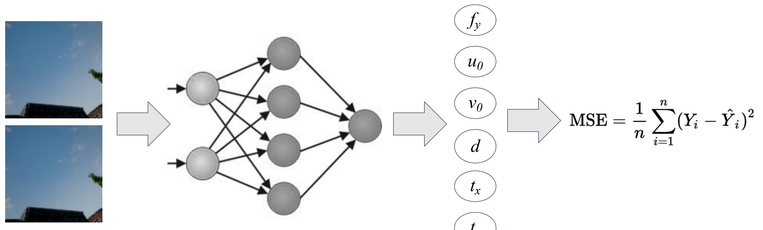
2D Point | Intrinsic | Rotation | Translation | 3D Point

Applications

3D Reconstruction

Autonomous Driving

2. Camera Calibration via End-to-end Learning

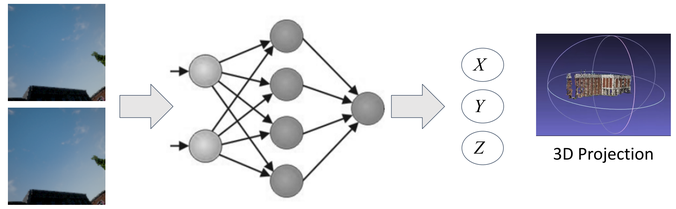


$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

d: Disparity

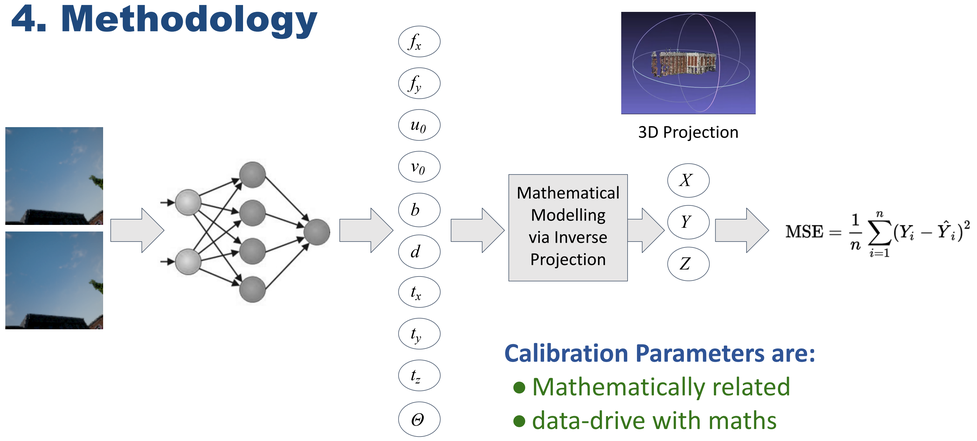
Parameters are:
- Mathematically unrelated
- Totally data-driven

3. 3D Reconstruction via End-to-end Learning



Parameters are:
- Mathematically unrelated
- Totally data-driven

4. Methodology



$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

Calibration Parameters are:
- Mathematically related
- data-drive with maths

Inverse Projection

Image->Camera->World

$$\begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix} \sim \begin{pmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}_{3\times1}^T & 1 \end{pmatrix}^{-1} \begin{pmatrix} f_x & 0 & u_0 \\ 0 & f_y & v_0 \\ 0 & 0 & 1 \end{pmatrix}^{-1} \begin{pmatrix} u \\ v \\ 1 \end{pmatrix}$$

Image->Camera

$$x_{cam} = f_x * b/d$$

$$y_{cam} = -(x_{cam}/f_x) * (u - u_0)$$

$$z_{cam} = (x_{cam}/f_y) * (v_0 - v)$$

Camera->World

$$X = x_{cam} * \cos\theta + z_{cam} * \sin\theta + t_x$$

$$Y = y_{cam} + t_y$$

$$Z = -x_{cam} * \sin\theta + z_{cam} * \cos\theta + t_z$$

5. Datasets

CVGL Camera Calibration Dataset
- Synthetic
- via CARLA Simulator
- 2 Towns
- 49 Camera Configurations
- 79,320 image pairs

Tsinghua-Daimler Cyclist Detection
- 2,914 images comprising of the test set used for evaluation

6. Results & Evaluation

Evaluation on CVGL Camera Calibration Dataset
- via Normalised Mean Absolute Error

Method	f_x	f_y	u_0	v_0	b	d	t_x	t_y	t_z	Θ
Average [1]	0.840	0.786	0.432	0.542	6.552	3.607	6.552	9.372	5.361	0.74
Deep-Homo [2]	0.062	0.062	0.008	0.008	0.156	0.065	0.156	0.161	0.155	0.05
MTL-CPL-U	0.935	0.685	0.892	0.737	0.938	0.432	0.400	0.329	0.432	1.06
MTL-Baseline	0.030	0.029	0.017	0.007	0.057	0.013	0.064	0.076	0.071	0.02
MTL-CPL-A	0.022	0.022	0.004	0.006	0.093	0.007	0.097	0.116	0.098	0.02

Evaluation on Tsinghua-Daimler Cyclist Detection Benchmark (without any training or transfer learning)
- via Normalised Mean Absolute Error

Method	f_x	f_y	u_0	v_0	b	d	t_x	t_y	t_z	Θ
Average [1]	0.994	0.991	0.969	0.951	112.438	0.492	10.843	271.935	13.798	982.41
Deep-Homo [2]	0.958	0.958	0.946	0.895	9.985	1.233	0.166	27.141	0.862	2746.99
MTL-CPL-U	0.872	0.888	0.782	0.795	0.081	1.271	0.147	23.836	0.635	7700.97
MTL-Baseline	0.957	0.958	0.944	0.893	18.323	1.258	1.035	32.946	0.999	2418.25
MTL-CPL-A	0.938	0.938	0.946	0.895	14.182	1.259	0.727	30.640	1.418	1995.35

1. Workman, Scott, et al. "Deepfocal: A method for direct focal length estimation." *2015 IEEE International Conference on Image Processing*. IEEE, 2015.
2. DeTone, Daniel, Tomasz Malisiewicz, and Andrew Rabinovich. "Deep image homography estimation." *arXiv preprint arXiv:1606.03798*, 2016.

7. Summary & Conclusions

- A new **dataset** for Camera Calibration.
- A **new representation** to incorporate camera model equations in a neural network in a multi-task learning framework.
- A new **loss utilising camera model** neural network to reconstruct 3D projection and uses the reconstruction loss to estimate the camera parameters.
- The proposed method **performs better** than both traditional and learning based methods.

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GitHub: https://github.com/thanif/CPL