



# Automatic Camera and Range Sensor Calibration using a single Shot

Andreas Geiger Frank Moosmann Ömer Car Bernhard Schuster

INSTITUTE OF MEASUREMENT AND CONTROL SYSTEMS KARLSRUHE INSTITUTE OF TECHNOLOGY









### **Overview**





Cameras / Microsoft Kinect

Cameras / Velodyne HDL-64

Setup: Video cameras (+ range sensor)

#### Goals

Calibrate cameras intrinsically and extrinsically

Register range sensor to cameras

### Overview

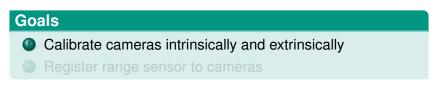




Cameras / Microsoft Kinect

Cameras / Velodyne HDL-64

Setup: Video cameras (+ range sensor)



### Overview





Cameras / Microsoft Kinect

Cameras / Velodyne HDL-64

Setup: Video cameras (+ range sensor)

#### Goals

- Calibrate cameras intrinsically and extrinsically
- Provide the sensor of the s

### **Proposed Method**



#### Contributions

- Automatic camera and range sensor calibration
- Our method requires only one image / scan per sensor
- Processing time < 5 minutes</p>

#### Assumptions

- Planar checkerboards (presented at different poses)
- Overlapping field of view (e.g., stereo)



## **Proposed Method**



#### Contributions

- Automatic camera and range sensor calibration
- Our method requires only one image / scan per sensor
- Processing time < 5 minutes</p>

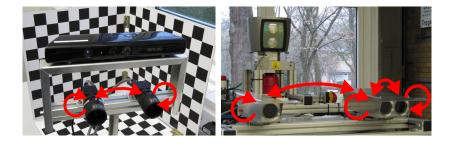
#### Assumptions

- Planar checkerboards (presented at different poses)
- Overlapping field of view (e.g., stereo)



### **Camera Calibration**





### Goals

Calibrate cameras intrinsically and extrinsically

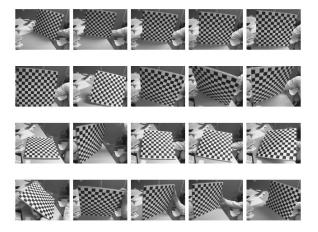
Register range sensor to cameras

A. Geiger - Camera and Range Sensor Calibration - www.cvlibs.net

### **Camera: Related Work**



#### Bouget's Camera Calibration Toolbox for Matlab / OpenCV

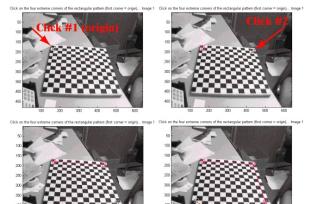


A. Geiger - Camera and Range Sensor Calibration - www.cvlibs.net

### **Camera: Related Work**



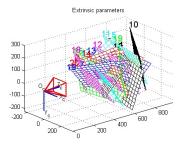
#### Bouget's Camera Calibration Toolbox for Matlab / OpenCV



### **Related Work: Camera Calibration**



#### Bouget's Camera Calibration Toolbox for Matlab / OpenCV



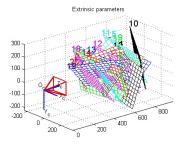
#### Requires $\geq$ 10 synchronized images

- No automatic corner detection and matching
- Time consuming

### **Related Work: Camera Calibration**



#### Bouget's Camera Calibration Toolbox for Matlab / OpenCV



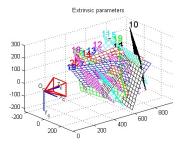
- Requires  $\geq$  10 synchronized images
- No automatic corner detection and matching

Time consuming

### **Related Work: Camera Calibration**



#### Bouget's Camera Calibration Toolbox for Matlab / OpenCV

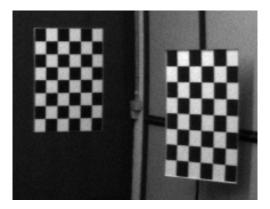


- Requires ≥ 10 synchronized images
- No automatic corner detection and matching
- Time consuming



### Corner detection and subpixel refinement

- Compute cornerness score for each pixel
- Non-maximum suppression, sub-pixel refinement

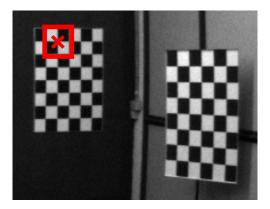


#### A. Geiger - Camera and Range Sensor Calibration - www.cvlibs.net



### Corner detection and subpixel refinement

- Compute cornerness score for each pixel
- Non-maximum suppression, sub-pixel refinement



#### A. Geiger - Camera and Range Sensor Calibration - www.cvlibs.net

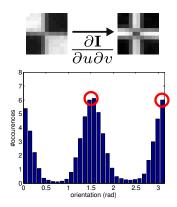


- Compute cornerness score for each pixel
- Non-maximum suppression, sub-pixel refinement



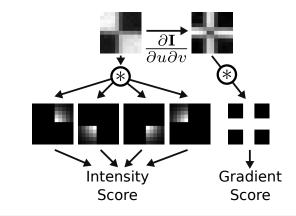


- Compute cornerness score for each pixel
- Non-maximum suppression, sub-pixel refinement



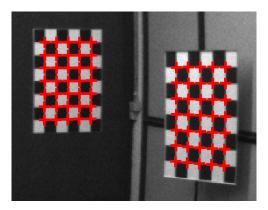


- Compute cornerness score for each pixel
- Non-maximum suppression, sub-pixel refinement

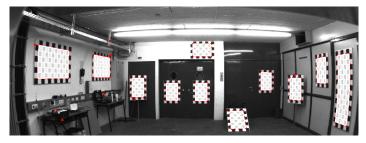




- Compute cornerness score for each pixel
- Non-maximum suppression, sub-pixel refinement







#### Parameters

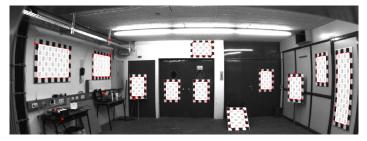
- Corner locations:  $\mathcal{X} = \{\mathbf{c}_1, .., \mathbf{c}_N\}, \mathbf{c}_i \in \mathbb{R}^2$
- Corner labels:  $\mathcal{Y} = \{\mathbf{y}_1, .., \mathbf{y}_N\}, \, \mathbf{y}_i \in \{\mathcal{O}\} \cup \mathbb{N}^3$

**Energy** 
$$E(\mathcal{X}, \mathcal{Y}) = E_{corners}(\mathcal{Y}) + E_{struct}(\mathcal{X}, \mathcal{Y})$$

 $E_{corners} = -$  number of explained corners

•  $E_{struct} = -$  corner collinearity





#### Parameters

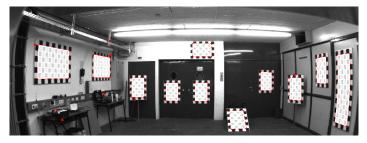
- Corner locations:  $\mathcal{X} = \{\mathbf{c}_1, .., \mathbf{c}_N\}, \mathbf{c}_i \in \mathbb{R}^2$
- Corner labels:  $\mathcal{Y} = \{\mathbf{y}_1, .., \mathbf{y}_N\}, \, \mathbf{y}_i \in \{\mathcal{O}\} \cup \mathbb{N}^3$

Energy 
$$E(\mathcal{X}, \mathcal{Y}) = E_{corners}(\mathcal{Y}) + E_{struct}(\mathcal{X}, \mathcal{Y})$$

 $E_{corners} = -$  number of explained corners

•  $E_{struct} = -$  corner collinearity





#### Parameters

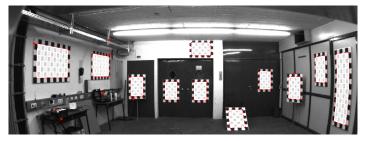
- Corner locations:  $\mathcal{X} = \{\mathbf{c}_1, .., \mathbf{c}_N\}, \mathbf{c}_i \in \mathbb{R}^2$
- Corner labels:  $\mathcal{Y} = \{\mathbf{y}_1, .., \mathbf{y}_N\}, \, \mathbf{y}_i \in \{\mathcal{O}\} \cup \mathbb{N}^3$

**Energy** 
$$E(\mathcal{X}, \mathcal{Y}) = E_{corners}(\mathcal{Y}) + E_{struct}(\mathcal{X}, \mathcal{Y})$$

• *E<sub>corners</sub>* = – number of explained corners

•  $E_{struct} = -$  corner collinearity





#### Parameters

- Corner locations:  $\mathcal{X} = \{\mathbf{c}_1, .., \mathbf{c}_N\}, \mathbf{c}_i \in \mathbb{R}^2$
- Corner labels:  $\mathcal{Y} = \{\mathbf{y}_1, .., \mathbf{y}_N\}, \, \mathbf{y}_i \in \{\mathcal{O}\} \cup \mathbb{N}^3$

**Energy** 
$$E(\mathcal{X}, \mathcal{Y}) = E_{corners}(\mathcal{Y}) + E_{struct}(\mathcal{X}, \mathcal{Y})$$

- *E<sub>corners</sub>* = number of explained corners
- $E_{struct} = -$  corner collinearity



Collinearity



Exponential complexity  $O(|\mathcal{X}|^{|\mathcal{L}|}) \Rightarrow$  Search space pruning

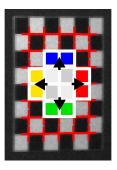
For each corner as seed do:





Exponential complexity  $O(|\mathcal{X}|^{|\mathcal{L}|}) \Rightarrow$  Search space pruning

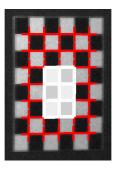
For each corner as seed do:





Exponential complexity  $O(|\mathcal{X}|^{|\mathcal{L}|}) \Rightarrow$  Search space pruning

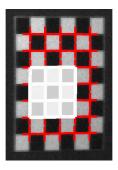
For each corner as seed do:





Exponential complexity  $O(|\mathcal{X}|^{|\mathcal{L}|}) \Rightarrow$  Search space pruning

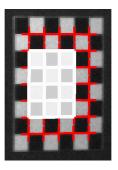
For each corner as seed do:





Exponential complexity  $O(|\mathcal{X}|^{|\mathcal{L}|}) \Rightarrow$  Search space pruning

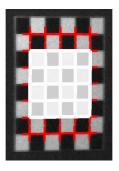
For each corner as seed do:





Exponential complexity  $O(|\mathcal{X}|^{|\mathcal{L}|}) \Rightarrow$  Search space pruning

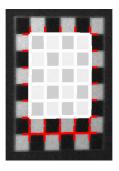
For each corner as seed do:





Exponential complexity  $O(|\mathcal{X}|^{|\mathcal{L}|}) \Rightarrow$  Search space pruning

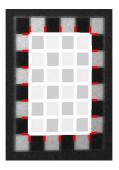
For each corner as seed do:





Exponential complexity  $O(|\mathcal{X}|^{|\mathcal{L}|}) \Rightarrow$  Search space pruning

For each corner as seed do:

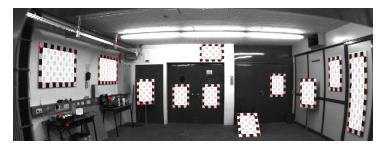




Exponential complexity  $O(|\mathcal{X}|^{|\mathcal{L}|}) \Rightarrow$  Search space pruning

For each corner as seed do:

- Incrementally add neighboring corners with lowest energy
- Keep lowest energy solutions in case of overlaps



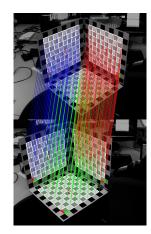
## **Camera: Matching and Optimization**



- Sample 2 checkerboards per image
- Compute similarity transformation from center of checkerboards
- Maximize number of inliers

#### Parameter Optimization

- Parameters: {f, c,  $\alpha$ ,  $k_1$ , ...,  $k_5$ }, {r, t}
- Non-linear least squares (Gauss-Newton)





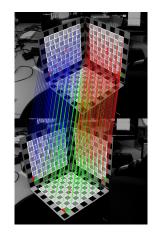
## **Camera: Matching and Optimization**



- Sample 2 checkerboards per image
- Compute similarity transformation from center of checkerboards
- Maximize number of inliers

#### **Parameter Optimization**

- Parameters: {f, c,  $\alpha$ ,  $k_1$ , ...,  $k_5$ }, {r, t}
- Non-linear least squares (Gauss-Newton)

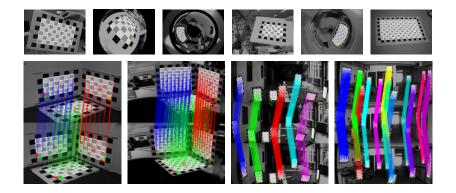






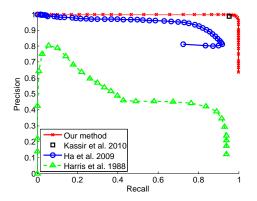
### **Results: Checkerboard Matching**





### **Results: Corner Detection**





### **Precision-Recall computed from**

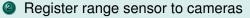
- 150 images taken under various conditions
- 80.000 checkerboard corners





#### Goals

Calibrate cameras intrinsically and extrinsically



A. Geiger - Camera and Range Sensor Calibration - www.cvlibs.net

# **3D Range Sensor: Related Work**

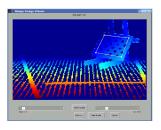


### [Unnikrishnan and Hebert 2005]

- Interactive GUI for laser-to-camera registration
- User marks calibration object manually

[Scaramuzza, Harati, Siegwart 2007]

- Registration of omnidirectional camera and laserscanner
- Manual correspondence selection required



# **3D Range Sensor: Related Work**

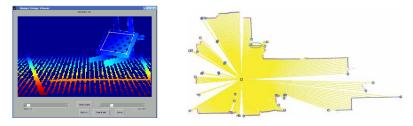


#### [Unnikrishnan and Hebert 2005]

- Interactive GUI for laser-to-camera registration
- User marks calibration object manually

### [Scaramuzza, Harati, Siegwart 2007]

- Registration of omnidirectional camera and laserscanner
- Manual correspondence selection required





- Compute normal vector  $\mathbf{n}_r^i \in \mathbb{R}^3$  for each point  $\mathbf{p}_r^i \in \mathbb{R}^3$  by principal component analysis on k-nearest neighbors
- Grow regions from random seeds
- Stop growing when normal gets too dissimilar from seed
- Repeat until segmentation covers all points



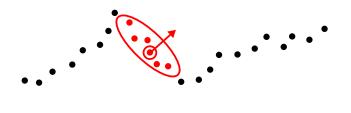


- Compute normal vector  $\mathbf{n}_r^i \in \mathbb{R}^3$  for each point  $\mathbf{p}_r^i \in \mathbb{R}^3$  by principal component analysis on k-nearest neighbors
- Grow regions from random seeds
- Stop growing when normal gets too dissimilar from seed
- Repeat until segmentation covers all points



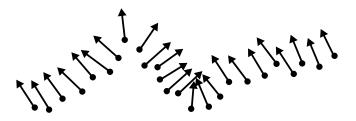


- Compute normal vector  $\mathbf{n}_r^i \in \mathbb{R}^3$  for each point  $\mathbf{p}_r^i \in \mathbb{R}^3$  by principal component analysis on k-nearest neighbors
- Grow regions from random seeds
- Stop growing when normal gets too dissimilar from seed
- Repeat until segmentation covers all points



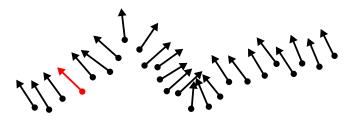


- Compute normal vector  $\mathbf{n}_r^i \in \mathbb{R}^3$  for each point  $\mathbf{p}_r^i \in \mathbb{R}^3$  by principal component analysis on k-nearest neighbors
- Grow regions from random seeds
- Stop growing when normal gets too dissimilar from seed
- Repeat until segmentation covers all points



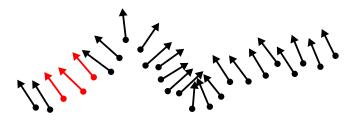


- Compute normal vector  $\mathbf{n}_r^i \in \mathbb{R}^3$  for each point  $\mathbf{p}_r^i \in \mathbb{R}^3$  by principal component analysis on k-nearest neighbors
- Grow regions from random seeds
- Stop growing when normal gets too dissimilar from seed
- Repeat until segmentation covers all points



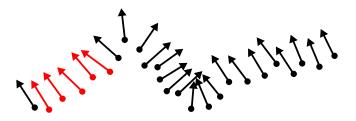


- Compute normal vector  $\mathbf{n}_r^i \in \mathbb{R}^3$  for each point  $\mathbf{p}_r^i \in \mathbb{R}^3$  by principal component analysis on k-nearest neighbors
- Grow regions from random seeds
- Stop growing when normal gets too dissimilar from seed
- Repeat until segmentation covers all points



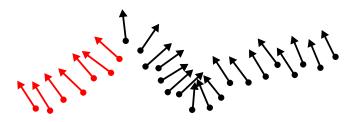


- Compute normal vector  $\mathbf{n}_r^i \in \mathbb{R}^3$  for each point  $\mathbf{p}_r^i \in \mathbb{R}^3$  by principal component analysis on k-nearest neighbors
- Grow regions from random seeds
- Stop growing when normal gets too dissimilar from seed
- Repeat until segmentation covers all points



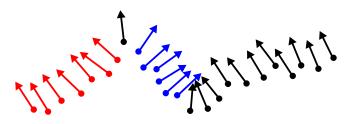


- Compute normal vector  $\mathbf{n}_r^i \in \mathbb{R}^3$  for each point  $\mathbf{p}_r^i \in \mathbb{R}^3$  by principal component analysis on k-nearest neighbors
- Grow regions from random seeds
- Stop growing when normal gets too dissimilar from seed
- Repeat until segmentation covers all points



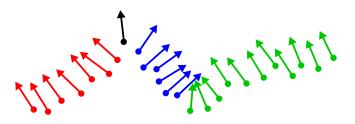


- Compute normal vector  $\mathbf{n}_r^i \in \mathbb{R}^3$  for each point  $\mathbf{p}_r^i \in \mathbb{R}^3$  by principal component analysis on k-nearest neighbors
- Grow regions from random seeds
- Stop growing when normal gets too dissimilar from seed
- Repeat until segmentation covers all points



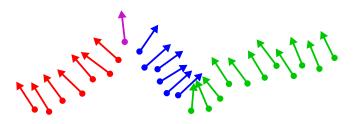


- Compute normal vector  $\mathbf{n}_r^i \in \mathbb{R}^3$  for each point  $\mathbf{p}_r^i \in \mathbb{R}^3$  by principal component analysis on k-nearest neighbors
- Grow regions from random seeds
- Stop growing when normal gets too dissimilar from seed
- Repeat until segmentation covers all points



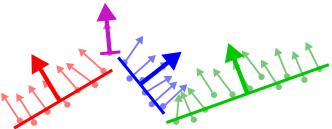


- Compute normal vector  $\mathbf{n}_r^i \in \mathbb{R}^3$  for each point  $\mathbf{p}_r^i \in \mathbb{R}^3$  by principal component analysis on k-nearest neighbors
- Grow regions from random seeds
- Stop growing when normal gets too dissimilar from seed
- Repeat until segmentation covers all points





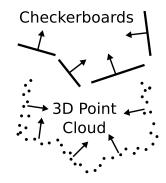
- Compute normal vector  $\mathbf{n}_r^i \in \mathbb{R}^3$  for each point  $\mathbf{p}_r^i \in \mathbb{R}^3$  by principal component analysis on k-nearest neighbors
- Grow regions from random seeds
- Stop growing when normal gets too dissimilar from seed
- Repeat until segmentation covers all points





### Sample a set of plausible hypotheses

- Draw 3 checkerboards
- Draw 3 segments
- Estimate optimal rotation R
- Estimate optimal translation t (minimize center to plane)
- Score hypothesis using euclidean distance
- Repeat until with probability p the correct solution has been found



Refine best hypotheses using robust Point-to-Point ICP

### Sample a set of plausible hypotheses

- Draw 3 checkerboards
- Draw 3 segments
- Estimate optimal rotation R
- Estimate optimal translation t (minimize center to plane)
- Score hypothesis using euclidean distance
- Repeat until with probability p the correct solution has been found

Refine best hypotheses using robust Point-to-Point ICP



### Sample a set of plausible hypotheses

- Draw 3 checkerboards
- Draw 3 segments
- Estimate optimal rotation R
- Estimate optimal translation t (minimize center to plane)
- Score hypothesis using euclidean distance
- Repeat until with probability p the correct solution has been found

Refine best hypotheses using robust Point-to-Point ICP

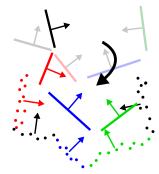


### Sample a set of plausible hypotheses

- Draw 3 checkerboards
- Draw 3 segments
- Estimate optimal rotation R
- Estimate optimal translation t (minimize center to plane)
- Score hypothesis using euclidean distance
- Repeat until with probability p the correct solution has been found

Refine best hypotheses using robust Point-to-Point ICP





### Sample a set of plausible hypotheses

- Draw 3 checkerboards
- Draw 3 segments
- Estimate optimal rotation R
- Estimate optimal translation t (minimize center to plane)
- Score hypothesis using euclidean distance
- Repeat until with probability p the correct solution has been found

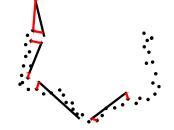
t -

Refine best hypotheses using robust Point-to-Point ICP



### Sample a set of plausible hypotheses

- Draw 3 checkerboards
- Draw 3 segments
- Estimate optimal rotation R
- Estimate optimal translation t (minimize center to plane)
- Score hypothesis using euclidean distance



 Repeat until with probability p the correct solution has been found

Refine best hypotheses using robust Point-to-Point ICP



### Sample a set of plausible hypotheses

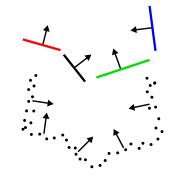
- Draw 3 checkerboards
- Draw 3 segments
- Estimate optimal rotation R
- Estimate optimal translation t (minimize center to plane)
- Score hypothesis using euclidean distance
- Repeat until with probability p the correct solution has been found



• Minimize:  $\sum_i w_i \|p_i - \mathcal{N}(p_i)\|_2$  with  $w_i \in \{0, 1\}$ 

#### A. Geiger - Camera and Range Sensor Calibration - www.cvlibs.net

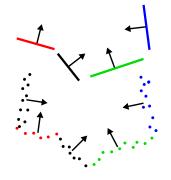




### Sample a set of plausible hypotheses

- Draw 3 checkerboards
- Draw 3 segments
- Estimate optimal rotation R
- Estimate optimal translation t (minimize center to plane)
- Score hypothesis using euclidean distance
- Repeat until with probability p the correct solution has been found



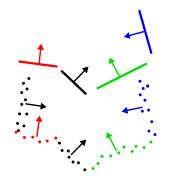




### Sample a set of plausible hypotheses

- Draw 3 checkerboards
- Draw 3 segments
- Estimate optimal rotation R
- Estimate optimal translation t (minimize center to plane)
- Score hypothesis using euclidean distance
- Repeat until with probability p the correct solution has been found

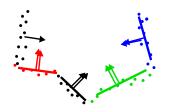






### Sample a set of plausible hypotheses

- Draw 3 checkerboards
- Draw 3 segments
- Estimate optimal rotation R
- Estimate optimal translation t (minimize center to plane)
- Score hypothesis using euclidean distance
- Repeat until with probability p the correct solution has been found

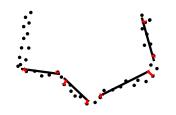


Refine best hypotheses using robust Point-to-Point ICP



### Sample a set of plausible hypotheses

- Draw 3 checkerboards
- Draw 3 segments
- Estimate optimal rotation R
- Estimate optimal translation t (minimize center to plane)
- Score hypothesis using euclidean distance
- Repeat until with probability p the correct solution has been found

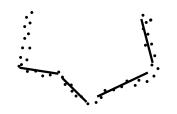


Refine best hypotheses using robust Point-to-Point ICP



### Sample a set of plausible hypotheses

- Draw 3 checkerboards
- Draw 3 segments
- Estimate optimal rotation R
- Estimate optimal translation t (minimize center to plane)
- Score hypothesis using euclidean distance
- Repeat until with probability p the correct solution has been found

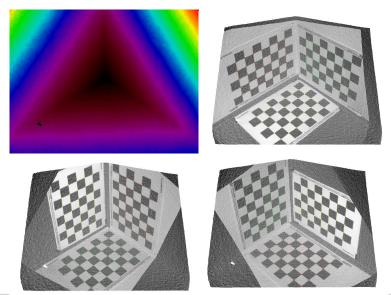


#### Refine best hypotheses using robust Point-to-Point ICP



### **3D Range Sensor: Results**

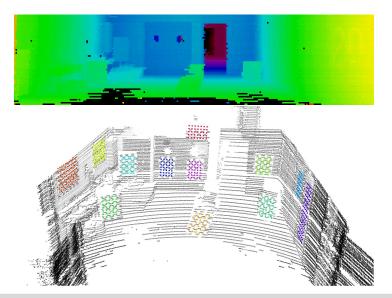




A. Geiger - Camera and Range Sensor Calibration - www.cvlibs.net

### **3D Range Sensor: Results**





A. Geiger - Camera and Range Sensor Calibration - www.cvlibs.net

### Thank you!







Previous Calculations Examples Home

#### Introduction

This online toolbox can be used to fully automatically calibrate one or multiple video cameras intrinsically and extrinsically using a single image per sensor only using a set of planar checkerboard calibration patterns. Furthermore, if provided, it registers the point cloud of a 3D laser range finder with respect to the first camera coordinate system. The main assumption for our algorithms to work is that all cameras and the range finder have a common field of view and the checkerboard patterns can be seen in all images, cover most parts of the images and are presented at various distances and orientations. Below, you can upload and calibrate your own data directly using our server. After a couple of minutes you will receive an email with your results. Please carefully read all the instructions on this page as well as our ICRA'12 publication before uploading any data to our server. You can also have a look at our example section, to get a guick overview over the data which needs to be submitted. Important note: Even though this toolbox is fully automatic it is an 'expert tool' and supposed to be used only by people which have a solid background in computer vision and camera calibration. If you are experienced and still have problems using this toolbox Left calibration image please write us a mail and we will check with your data.









