



Chapter 8

Direct Approaches to Visual SLAM

Multiple View Geometry
Summer 2015

Direct Methods

Realtime Dense
Geometry

Dense RGB-D
Tracking

Loop Closure and
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Dense Tracking and
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Classical Approaches to Multiple View Reconstruction

In the past chapters we have studied **classical approaches to multiple view reconstruction**. These methods tackle the problem of structure and motion estimation (or visual SLAM) in several steps:

- 1 A set of **feature points** is extracted from the images – ideally points such as **corners** which can be reliably identified in subsequent images as well.
- 2 One determines a **correspondence of these points across the various images**. This can be done either through local tracking (using optical flow approaches) or by random sampling of possible partners based on a feature descriptor (SIFT, SURF, etc.) associated with each point.
- 3 The **camera motion is estimated** based on a set of corresponding points. In many approaches this is done by a series of algorithms such as the **eight-point algorithm** or the five-point algorithm followed by **bundle adjustment**.
- 4 For a given camera motion one can then compute a **dense reconstruction** using photometric stereo approaches.



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Shortcomings of Classical Approaches

Such classical approaches are **indirect** in the sense that they do not compute structure and motion directly from the images but rather from a sparse set of precomputed feature points. Despite a number of successes, they have several drawbacks:

- From the point of view of statistical inference, they are **suboptimal**: In the selection of feature points much potentially valuable information contained in the colors of each image is discarded.
- They invariably **lack robustness**: Errors in the point correspondence may have devastating effects on the estimated camera motion. Since one often selects very few point pairs only (8 points for the eight-point algorithm, 5 points for the five-point algorithm), any incorrect correspondence will lead to an incorrect motion estimate.
- They do not address the **highly coupled problems of motion estimation and dense structure estimation**. They merely do so for a sparse set of points. As a consequence, improvements in the estimated dense geometry will not be used to improve the camera motion estimates.



Toward Direct Approaches to Multiview Reconstruction

In the last few years, researchers have been promoting **direct approaches to multi-view reconstruction**. Rather than extracting a sparse set of feature points to determine the camera motion, **direct methods aim at estimating camera motion and dense or semi-dense scene geometry directly from the input images**. This has several advantages:

- Direct methods tend to be **more robust** to noise and other nuisances because they **exploit all available input information**.
- Direct methods provide a **semi-dense geometric reconstruction** of the scene which goes well beyond the sparse point cloud generated by the eight-point algorithm or bundle adjustment. Depending on the application, a separate dense reconstruction step may no longer be necessary.
- Direct methods are **typically faster** because the feature-point extraction and correspondence finding is omitted: They can provide fairly accurate camera motion and scene structure in real-time on a CPU.



Feature-Based versus Direct Methods



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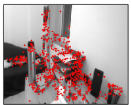
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Feature-Based

Input Images



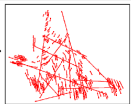
Extract & Match Features
(SIFT / SURF / ...)



abstract image to feature observations

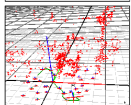
Track:

min. **reprojection** error
(point distances)



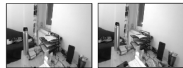
Map:

est. feature-parameters
(3D points / normals)



Direct

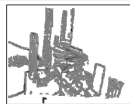
Input Images



keep full images (no abstraction)

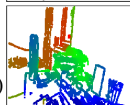
Track:

min. **photometric** error
(intensity differences)



Map:

est. per-pixel depth
(semi-dense depth map)



Direct Methods for Multi-view Reconstruction



In the following, we will briefly review several recent works on direct methods for multiple-view reconstruction:

- the method of [Stühmer, Gumhold, Cremers, DAGM 2010](#) which computes dense geometry from a handheld camera in real-time. For given camera motions, the dense reconstruction problem is computed directly from the images.
- the methods of [Steinbrücker, Sturm, Cremers, 2011](#) and [Kerl, Sturm, Cremers, 2013](#) which directly compute the camera motion of an RGB-D camera without feature extraction.
- the method of [Newcombe, Lovegrove, Davison, ICCV 2011](#) which directly determines dense geometry and camera motion from the images.
- the method of [Engel, Sturm, Cremers ICCV 2013](#) and [Engel, Schöps, Cremers ECCV 2014](#) which directly computes camera motion and semi-dense geometry for a handheld (monocular) camera.

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Realtime Dense Geometry from a Handheld Camera

Let $g_i \in SE(3)$ be the rigid body motion from the first camera to the i -th camera, and let $l_i : \Omega \rightarrow \mathbb{R}$ be the i -th image. A **dense depth map** $h : \Omega \rightarrow \mathbb{R}$ can be computed by solving the optimization problem:

$$\min_h \sum_{i=2}^n \int_{\Omega} |l_1(x) - l_i(\pi g_i(hx))| dx + \lambda \int_{\Omega} |\nabla h| dx,$$

where x is represented in homogeneous coordinates and hx is the corresponding 3D point.

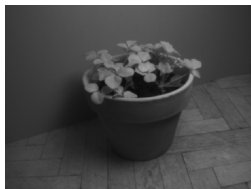
Like in optical flow estimation, the unknown depth map should be such that for all pixels $x \in \Omega$, the transformation into the other images l_i should give rise to the same color as in the reference image l_1 .

This cost function can be minimized at framerate by **coarse-to-fine linearization** solved in parallel on a GPU.

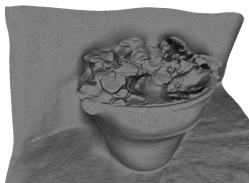
Stuehmer, Gumhold, Cremers, DAGM 2010.



Realtime Dense Geometry from a Handheld Camera



Input image



Reconstruction



Textured geometry



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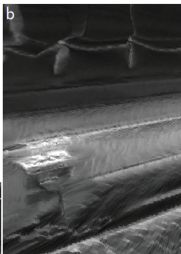
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Textured reconstructions



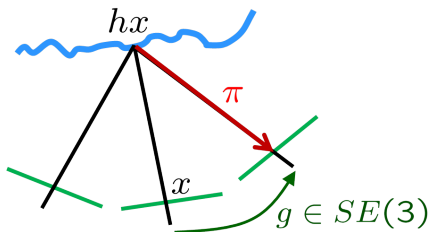
Untextured

Stuehmer, Gumhold, Cremers, DAGM 2010.

Dense RGB-D Tracking

The approach of Stühmer et al. (2010) relies on a sparse feature-point based camera tracker (PTAM) and computes dense geometry directly on the images. Steinbrücker, Sturm, Cremers (2011) propose a complementary approach to directly compute the camera motion from RGB-D images. The idea is to compute the rigid body motion g_ξ which optimally aligns two subsequent color images I_1 and I_2 :

$$\min_{\xi \in \mathfrak{se}(3)} \int_{\Omega} |I_1(x) - I_2(\pi g_\xi(hx))|^2 dx$$



Dense RGB-D Tracking

The above non-convex problem can be approximated as a convex problem by linearizing the residuum around an initial guess ξ_0 :

$$E(\xi) \approx \int_{\Omega} \left| I_1(x) - I_2(\pi g_{\xi_0}(hx)) - \nabla I_2^T \left(\frac{d\pi}{dg_{\xi}} \right) \left(\frac{dg_{\xi}}{d\xi} \right) \xi \right|^2 dx$$

This is a convex quadratic cost function which gives rise to a linear optimality condition:

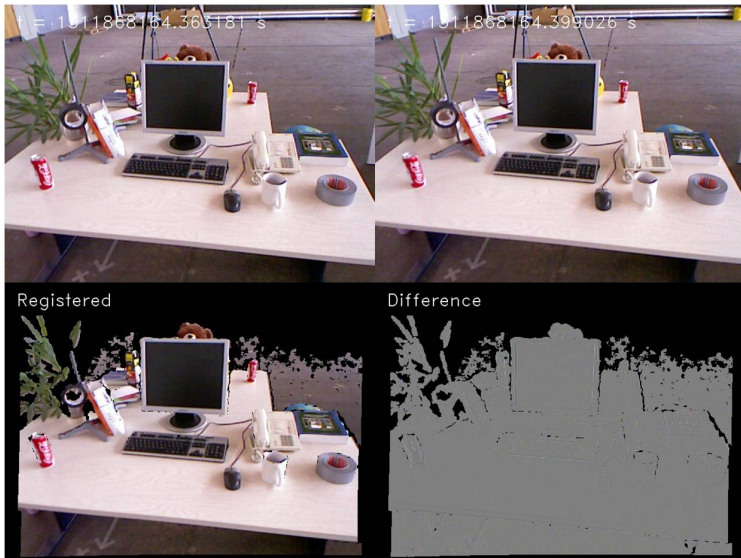
$$\frac{dE(\xi)}{d\xi} = A\xi + b = 0$$

To account for larger motions of the camera, this problem is solved in a coarse-to-fine manner. The linearization of the residuum is identical with a Gauss-Newton approach. It corresponds to an approximation of the Hessian by a positive definite matrix.

Steinbrücker, Sturm, Cremers 2011



Dense RGB-D Tracking



Steinbrücker, Sturm, Cremers 2011

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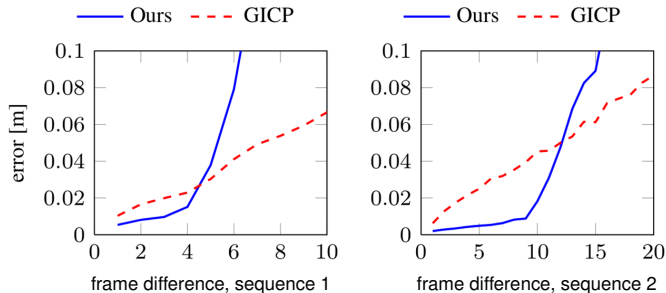
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Dense RGB-D Tracking

In the small-baseline setting, this image aligning approach provides more accurate camera motion than the commonly used generalized Iterated Closest Points (GICP) approach.



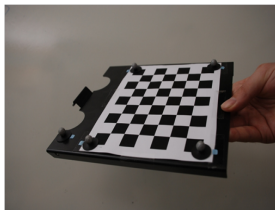
Steinbrücker, Sturm, Cremers 2011

A related direct tracking approach was proposed for stereo reconstruction in [Comport, Malis, Rives, ICRA 2007](#). A generalization which makes use of [non-quadratic penalizers](#) was proposed in [Kerl, Sturm, Cremers, ICRA 2013](#).



A Benchmark for RGB-D Tracking

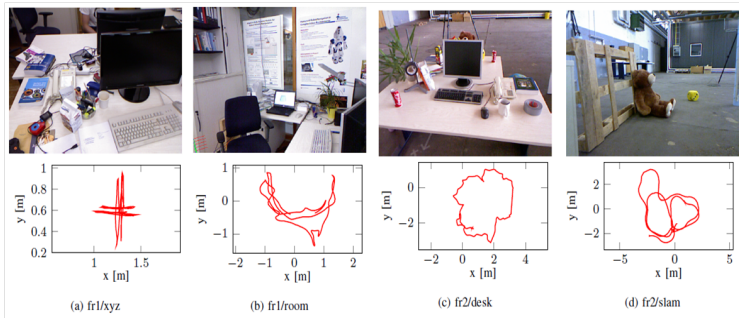
Accurately tracking the camera is among the most central challenges in computer vision. Quantitative performance of algorithms can be validated on benchmarks.



Sturm, Engelhard, Endres, Burgard, Cremers, IROS 2012



A Benchmark for RGB-D Tracking



Sturm, Engelhard, Endres, Burgard, Cremers, IROS 2012

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Combining Photometric and Geometric Consistency

Kerl, Sturm, Cremers, IROS 2013 propose an extension of the RGB-D camera tracker which combines **color consistency** and **geometric consistency** of subsequent RGB-D images.

Assuming that the vector $r_i = (r_{ci}, r_{zi}) \in \mathbb{R}^2$ containing the color and geometric discrepancy for pixel i follows a **bivariate t-distribution**, the maximum likelihood pose estimate can be computed as:

$$\min_{\xi \in \mathbb{R}^6} \sum_i w_i r_i^\top \Sigma^{-1} r_i,$$

with weights w_i based on the student t-distribution:

$$w_i = \frac{\nu + 1}{\nu + r_i^\top \Sigma^{-1} r_i}.$$

This nonlinear weighted least squares problem can be solved in an iteratively reweighted least squares manner by alternating a **Gauss-Newton style optimization** with a **re-estimation of the weights w_i and the matrix Σ** .



Loop Closure and Global Consistency



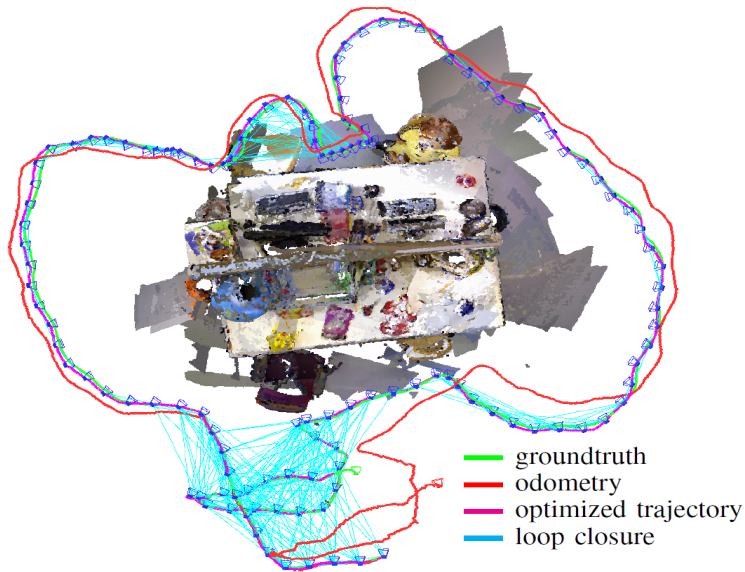
When tracking a camera over a longer period of time, **errors tend to accumulate**. While a single room may still be mapped more or less accurately, mapping a larger environment will lead to increasing distortions: Corridors and walls will no longer be straight but slightly curved.

A remedy is to introduce **loop closure**, a technique popularized in laser-based SLAM systems. The key idea is to estimate the relative camera motion $\hat{\xi}_{ij}$ for any camera pair i and j in a certain neighborhood. Subsequently, one can determine a **globally consistent camera trajectory** $\xi = \{\xi_i\}_{i=1..T}$ by solving the **nonlinear least squares problem**

$$\min_{\xi} \sum_{i \sim j} \left(\hat{\xi}_{ij} - \xi_i \circ \xi_j^{-1} \right)^T \Sigma_{ij} \left(\hat{\xi}_{ij} - \xi_i \circ \xi_j^{-1} \right),$$

where Σ_{ij} denotes the uncertainty of measurement $\hat{\xi}_{ij}$. This problem can be solved using, for example, a **Levenberg-Marquardt algorithm**.

Loop Closure and Global Consistency



Kerl, Sturm, Cremers, IROS 2013



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Dense Tracking and Mapping

Newcombe, Lovegrove & Davison (ICCV 2011) propose an algorithm which computes both the geometry of the scene and the camera motion from a direct and dense algorithm.

They compute the **inverse depth** $u = 1/h$ by minimizing a cost function of the form

$$\min_u \sum_{i=2}^n \int_{\Omega} \left| I_1(x) - I_i \left(\pi g_i \left(\frac{x}{u} \right) \right) \right| dx + \lambda \int_{\Omega} \rho(x) |\nabla u| dx,$$

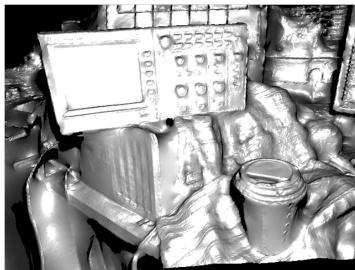
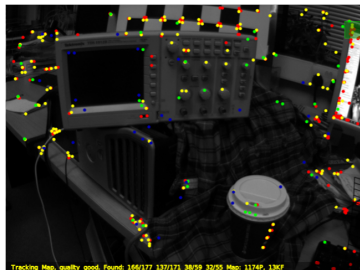
for fixed camera motions g_i . The function ρ introduces an **edge-dependent weighting** assigning small weights in locations where the input images exhibit strong gradients:

$$\rho(x) = \exp(-|\nabla I_{\sigma}(x)|^{\alpha}).$$

The **camera tracking** is then performed **with respect to the textured reconstruction** in a manner similar to Steinbrücker et al. (2011). The method is initialized using feature point based stereo.



Dense Tracking and Mapping



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Newcombe, Lovegrove & Davison (ICCV 2011)

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A method for real-time direct monocular SLAM is proposed in Engel, Sturm, Cremers, ICCV 2013 and Engel, Schöps, Cremers, ECCV 2014. It combines several contributions which make it well-suited for robust large-scale monocular SLAM:

- Rather than tracking and putting into correspondence a sparse set of feature points, the method estimates a **semi-dense depth map** which associates an inverse depth with each pixel that exhibits sufficient gray value variation.
- To account for noise and uncertainty each inverse depth value is associated with an **uncertainty** which is **propagated and updated over time** like in a Kalman filter.
- Since monocular SLAM is invariably defined up to scale only, we explicitly facilitate scaling of the reconstruction by modeling the camera motion using the **Lie group of 3D similarity transformations $Sim(3)$** .
- Global consistency is assured by **loop closing on $Sim(3)$** .

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Tracking by Direct $sim(3)$ Image Alignment

Since reconstructions from a monocular camera are only defined up to scale, Engel, Schöps, Cremers, ECCV 2014 account for rescaling of the environment by representing the camera motion as an element in the Lie group of 3D similarity transformations $Sim(3)$ which is defined as:

$$Sim(3) = \left\{ \left(\begin{array}{cc} sR & T \\ 0 & 1 \end{array} \right) \text{ with } R \in SO(3), T \in \mathbb{R}^3, s \in \mathbb{R}_+ \right\}.$$

One can minimize a nonlinear least squares problem

$$\min_{\xi \in sim(3)} \sum_i w_i r_i^2(\xi),$$

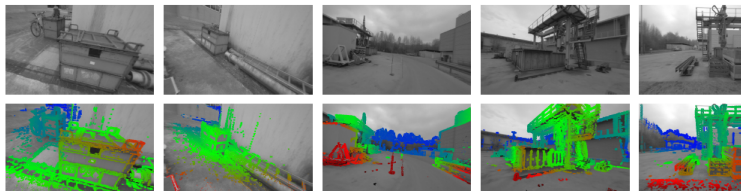
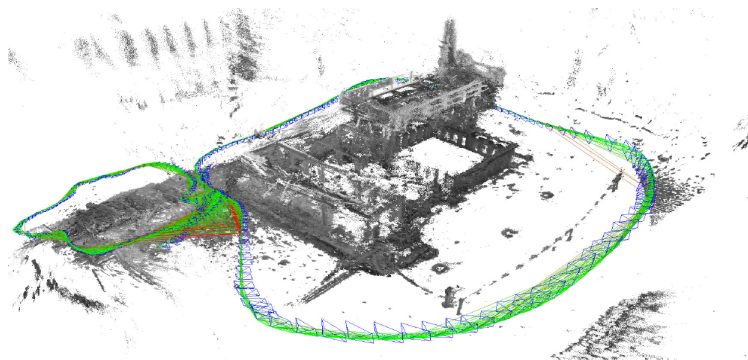
where r_i denotes the color residuum across different images and w_i a weighting as suggested in Kerl et al. IROS 2013.

The above cost function can then be optimized by a weighted Gauss-Newton algorithm on the Lie group $Sim(3)$:

$$\xi^{(t+1)} = \Delta_\xi \circ \xi^{(t)}, \quad \text{with } \Delta_\xi = (J^\top W J)^{-1} J^\top W r, \quad J = \frac{\partial r}{\partial \xi}$$



Large-Scale Direct Monocular SLAM



Engel, Schöps, Cremers, ECCV 2014

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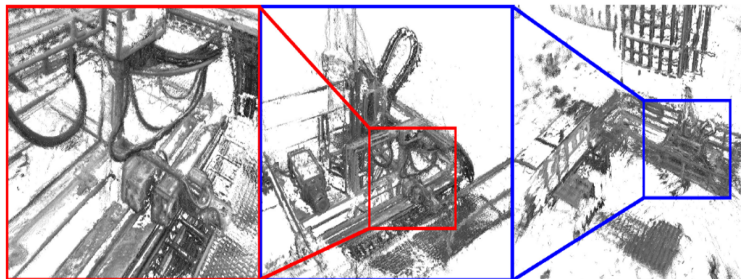
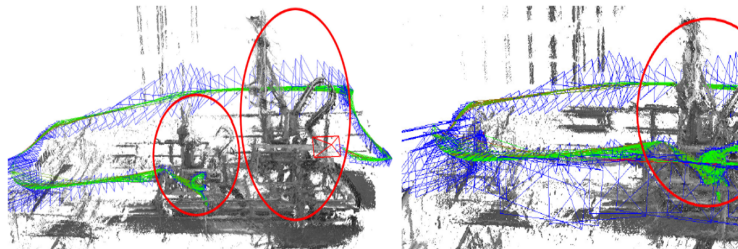
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Engel, Schöps, Cremers, ECCV 2014