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Robotic 3D Vision

Lecture 8: Visual Odometry 3 –Direct Methods

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What We Will Cover Today

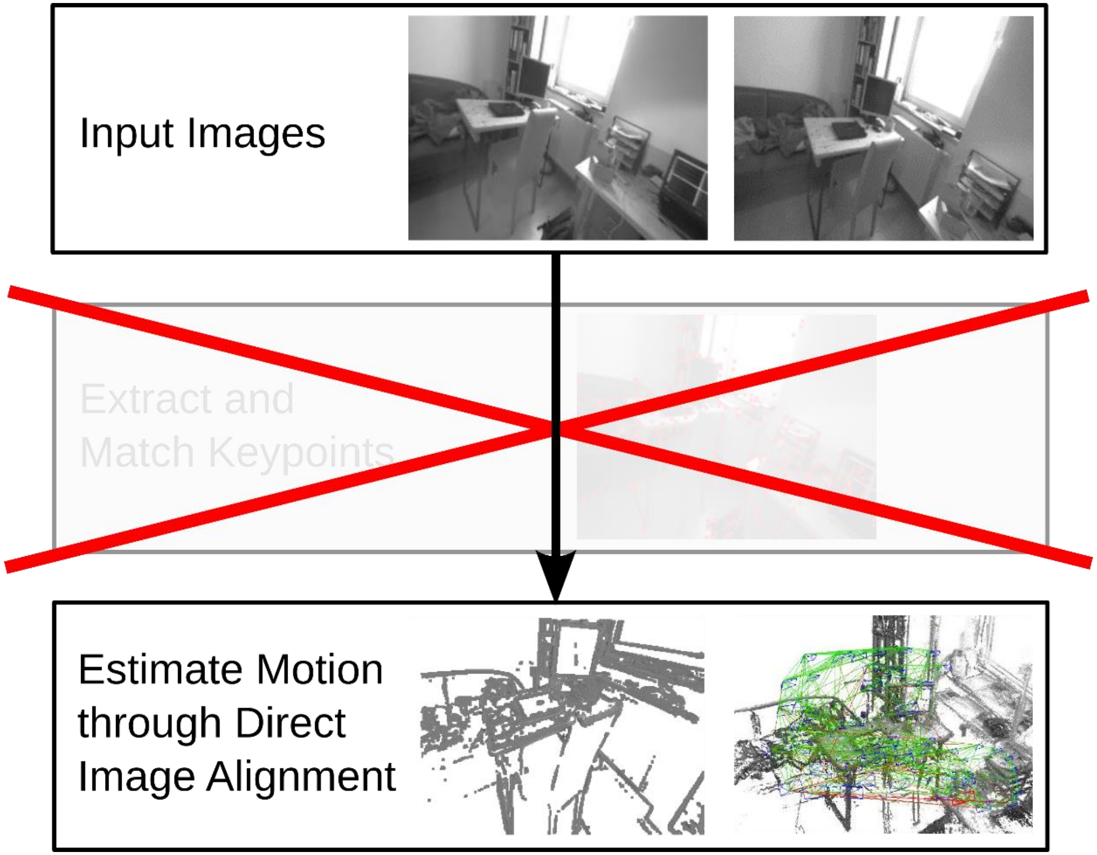
- Direct visual odometry methods
  - Principles of direct image alignment
  - Photometric alignment
  - Geometric alignment
- Direct visual odometry for RGB-D cameras
- Direct visual odometry for monocular cameras
  - Semi-dense monocular odometry
- Photometric calibration
- Stereo extensions

Direct Visual Odometry Pipeline

- Avoid manually designed keypoint detection and matching
- Instead: direct image alignment

$$E(\boldsymbol{\xi}) = \int_{\mathbf{u}\in\Omega} |\mathbf{I}_1(\mathbf{u}) - \mathbf{I}_2(\omega(\mathbf{u},\boldsymbol{\xi}))| \, d\mathbf{u}$$

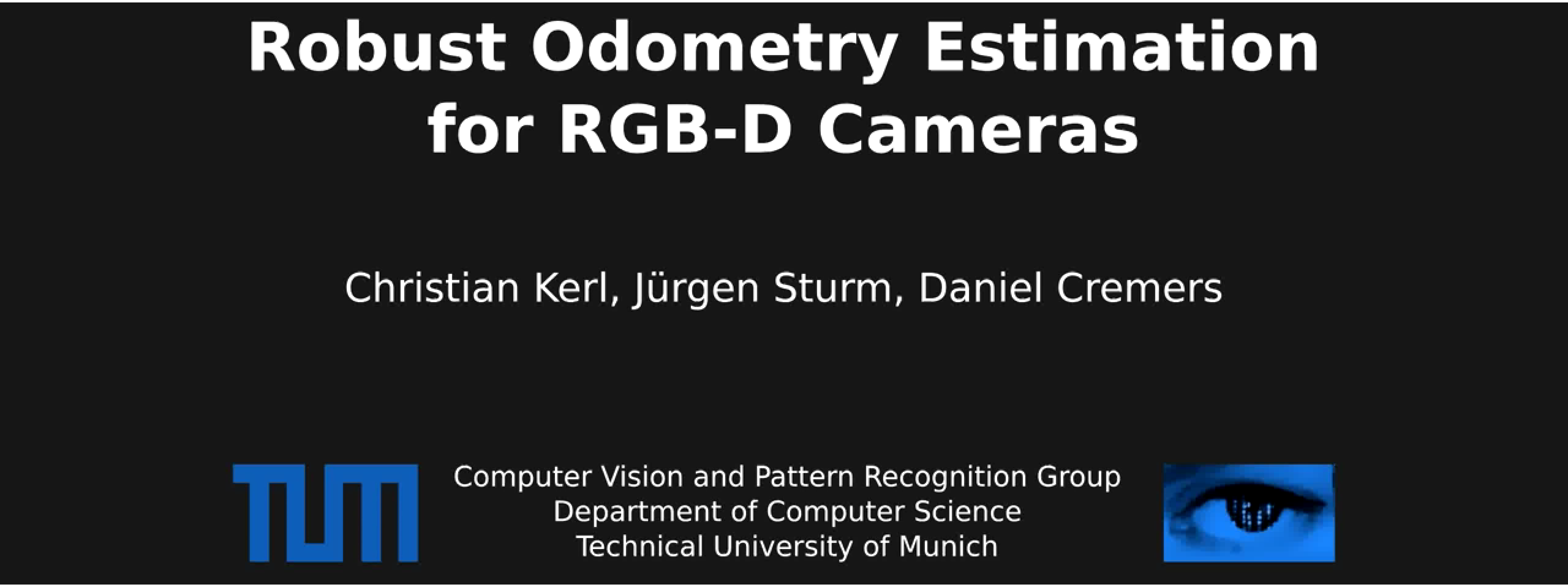
- Warping requires depth
  - RGB-D
  - Fixed-baseline stereo
  - Temporal stereo, tracking and (local) mapping


Input Images

~~Extract and Match Keypoints~~

Estimate Motion through Direct Image Alignment

Direct Visual Odometry Example (RGB-D)



Robust Odometry Estimation for RGB-D Cameras

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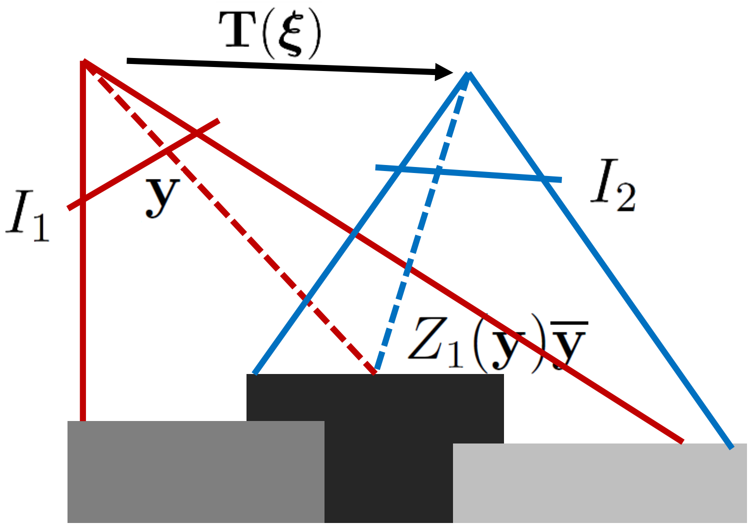
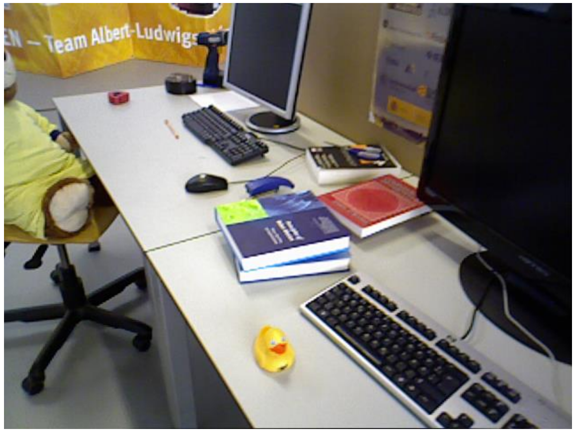
Direct Image Alignment Principle


$\mathbf{T}(\boldsymbol{\xi})$
I_1
$\mathbf{y}$
I_2
$Z_1(\mathbf{y})\overline{\mathbf{y}}$

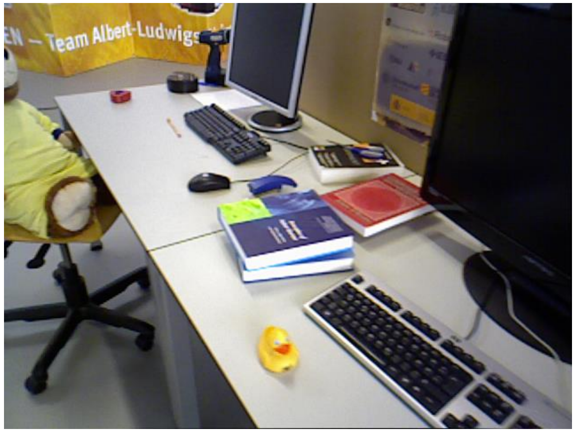
- If we know pixel depth, we can „simulate“ an image from a different view point
- Ideally, the warped image is the same as the image taken from that pose:

$$I_1\left(\mathbf{y}\right) = I_2\left(\pi\left(\mathbf{T}(\boldsymbol{\xi})Z_1(\mathbf{y})\overline{\mathbf{y}}\right)\right)$$

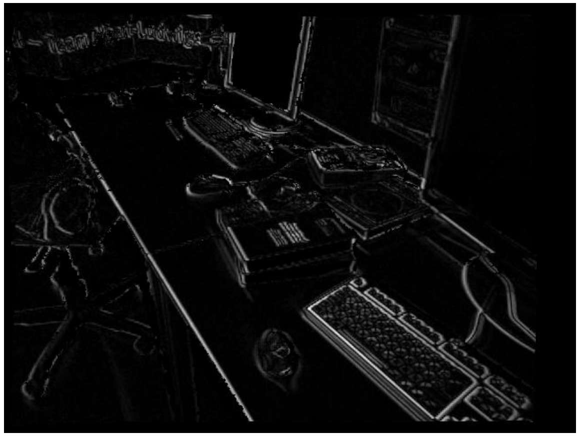
Derivative of Image Warp



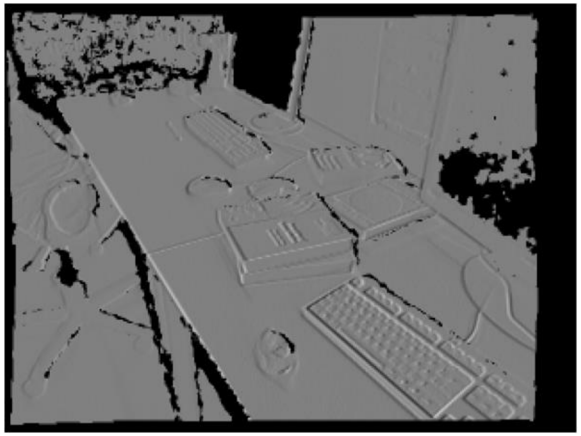
I_1



I_2



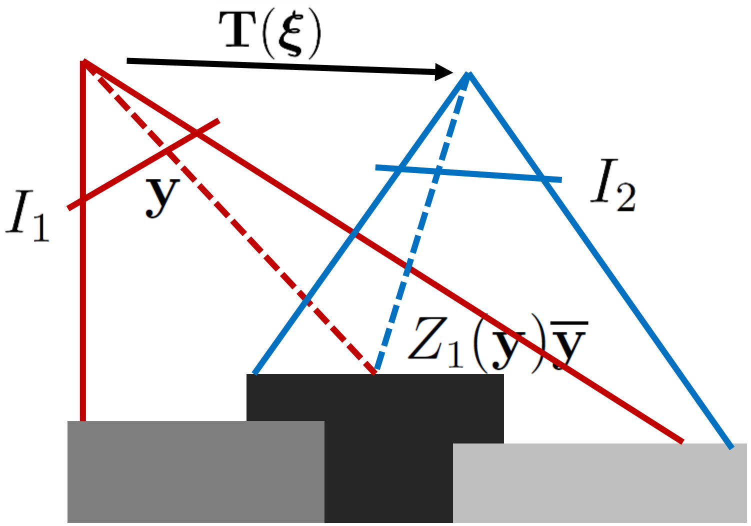
I_1 - I_2



$$\left.\frac{\partial I_2\left(\pi\left(\mathbf{T}(\boldsymbol{\xi}) Z_1(\mathbf{y})\overline{\mathbf{y}}\right)\right)}{\partial v_x}\right|_{\boldsymbol{\xi}=\mathbf{0}}$$

Images from Kerl et al., ICRA 2013

Direct RGB-D Image Alignment


$\mathbf{T}(\boldsymbol{\xi})$
I_1
$\mathbf{y}$
I_2
$Z_1(\mathbf{y})\overline{\mathbf{y}}$

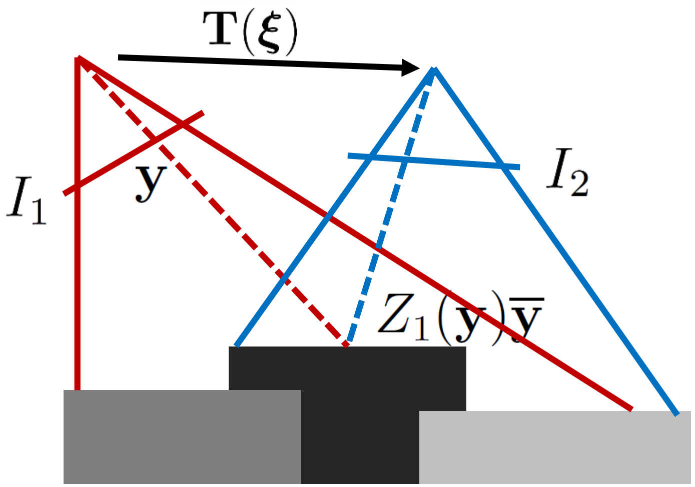
- RGB-D cameras measure depth, we only need to estimate camera motion!
- In addition to the photometric error

$$I_1(\mathbf{y}) = I_2\left(\pi\left(\mathbf{T}(\boldsymbol{\xi})Z_1(\mathbf{y})\overline{\mathbf{y}}\right)\right)$$

we can measure geometric error directly

$$\left[\mathbf{T}(\boldsymbol{\xi})Z_1(\mathbf{y})\overline{\mathbf{y}}\right]_z = Z_2\left(\pi\left(\mathbf{T}(\boldsymbol{\xi})Z_1(\mathbf{y})\overline{\mathbf{y}}\right)\right)$$

Probabilistic Direct Image Alignment


$\mathbf{T}(\boldsymbol{\xi})$
I_1
$\mathbf{y}$
I_2
$Z_1(\mathbf{y})\overline{\mathbf{y}}$

- Measurements are affected by noise

$$I_1\left(\mathbf{y}\right) = I_2\left(\pi\left(\mathbf{T}(\boldsymbol{\xi})Z_1(\mathbf{y})\overline{\mathbf{y}}\right)\right) + \epsilon$$

- A convenient assumption is Gaussian noise

$$\epsilon \sim \mathcal{N}(0, \sigma_I^2)$$

- If we further assume that pixel measurements are stochastically independent, we can formulate the a-posteriori probability

$$p(\boldsymbol{\xi} \mid I_1, I_2) \propto p(I_1 \mid \boldsymbol{\xi}, I_2)p(\boldsymbol{\xi})$$

$$\propto p(\boldsymbol{\xi}) \prod_{\mathbf{y}\in\Omega} \mathcal{N}\left(I_1\left(\mathbf{y}\right) - I_2\left(\pi\left(\mathbf{T}(\boldsymbol{\xi})Z_1(\mathbf{y})\overline{\mathbf{y}}\right)\right); 0, \sigma_I^2\right)$$

Optimization Approach

- Optimize negative log-likelihood
  - Product of exponentials becomes a summation over quadratic terms
  - Normalizers are independent of the pose

$$E(\boldsymbol{\xi}) = \sum_{\mathbf{y} \in \Omega} \frac{r(\mathbf{y}, \boldsymbol{\xi})^2}{\sigma_I^2}$$, stacked residuals: $$E(\boldsymbol{\xi}) = \mathbf{r}(\boldsymbol{\xi})^\top \mathbf{W} \mathbf{r}(\boldsymbol{\xi})$$

$$r(\mathbf{y}, \boldsymbol{\xi}) = I_1(\mathbf{y}) - I_2\left(\pi\left(\mathbf{T}(\boldsymbol{\xi}) Z_1(\mathbf{y}) \overline{\mathbf{y}}\right)\right)$$

- Non-linear least squares problem can be efficiently optimized using standard second-order tools (Gauss-Newton, Levenberg-Marquardt)

Recap: Gauss-Newton Method

- Approximate Newton's method to minimize E(x)
  - Approximate E(x) through linearization of residuals

$$\begin{aligned}\widetilde{E}(\mathbf{x}) &= \frac{1}{2}\widetilde{\mathbf{r}}(\mathbf{x})^\top \mathbf{W}\widetilde{\mathbf{r}}(\mathbf{x}) \\ &= \frac{1}{2}\left(\mathbf{r}(\mathbf{x}_k) + \mathbf{J}_k\left(\mathbf{x} - \mathbf{x}_k\right)\right)^\top \mathbf{W}\left(\mathbf{r}(\mathbf{x}_k) + \mathbf{J}_k\left(\mathbf{x} - \mathbf{x}_k\right)\right) \qquad \mathbf{J}_k := \nabla_{\mathbf{x}}\mathbf{r}(\mathbf{x})\big|_{\mathbf{x}=\mathbf{x}_k} \\ &= \frac{1}{2}\mathbf{r}(\mathbf{x}_k)^\top \mathbf{W}\mathbf{r}(\mathbf{x}_k) + \underbrace{\mathbf{r}(\mathbf{x}_k)^\top \mathbf{W}\mathbf{J}_k}_{=:\mathbf{b}_k^\top}\left(\mathbf{x} - \mathbf{x}_k\right) + \frac{1}{2}\left(\mathbf{x} - \mathbf{x}_k\right)^\top \underbrace{\mathbf{J}_k^\top \mathbf{W}\mathbf{J}_k}_{=:\mathbf{H}_k}\left(\mathbf{x} - \mathbf{x}_k\right)\end{aligned}$$

  - Find root of $\nabla_{\mathbf{x}}\widetilde{E}(\mathbf{x}) = \mathbf{b}_k^\top + \left(\mathbf{x} - \mathbf{x}_k\right)^\top \mathbf{H}_k$ using Newton's method, i.e.

$$\nabla_{\mathbf{x}}\widetilde{E}(\mathbf{x}) = \mathbf{0} \text{ iff } \mathbf{x} = \mathbf{x}_k - \mathbf{H}_k^{-1}\mathbf{b}_k$$

- Pros:
  - Faster convergence (approx. quadratic convergence rate)
- Cons:
  - Divergence if too far from local optimum (H not positive definite)
  - Solution quality depends on initial guess

Recap: Levenberg-Marquardt Method

- Gradually transition between gradient descent and Gauss-Newton
  - Augment Hessian approximation of Gauss-Newton (damping)

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \left(\mathbf{H}_k + \lambda \mathbf{I}\right)^{-1} \mathbf{b}_k$$

  - Adaptive weighting: $\mathbf{x}_{k+1} = \mathbf{x}_k - \left(\mathbf{H}_k + \lambda \, \mathrm{diag}(\mathbf{H}_k)\right)^{-1} \mathbf{b}_k$
  - Start with $\lambda = 0.1$
  - Accept step and decrease lambda $\lambda \leftarrow \lambda/2$ if error function decreases, otherwise discard step and increase lambda $\lambda \leftarrow 2\lambda$ (akin line search)

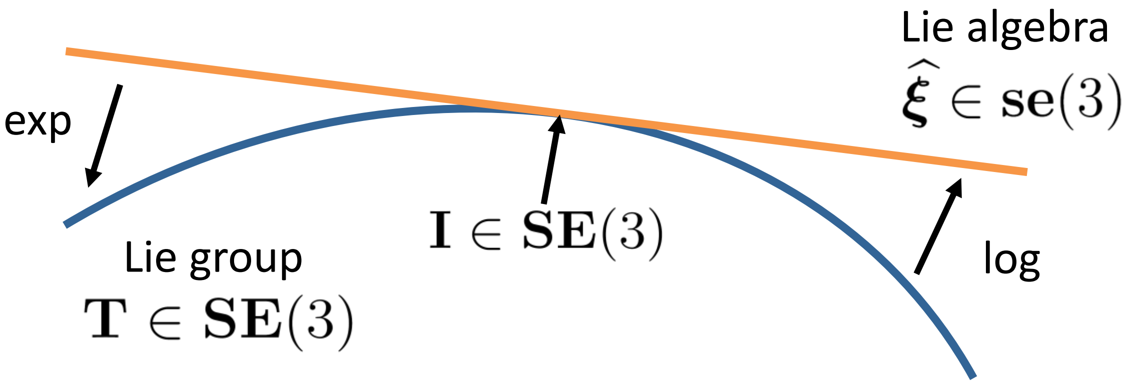
- Pros:
  - Fast convergence close to local optimum (quadratic convergence rate close to optimum)
  - More stable but slow convergence far from local optimum
- Cons:
  - Solution quality depends on initial guess

Pose Parametrization for Optimization

- Requirements on pose parametrization
  - No singularities
  - Minimal to avoid constraints

- Various pose parametrizations available
  - Direct matrix representation => not minimal
  - Quaternion / translation => not minimal
  - Euler angles / translation => singularities
  - Twist coordinates of elements in Lie Algebra se(3) of SE(3) (axis-angle / translation)

Recap: Representing Motion using Lie Algebra se(3)


Lie algebra
$\widehat{\boldsymbol{\xi}} \in \mathbf{se}(3)$
exp
$\mathbf{I} \in \mathbf{SE}(3)$
log
Lie group
$\mathbf{T} \in \mathbf{SE}(3)$

$$\boldsymbol{\xi} := \begin{pmatrix} \boldsymbol{\omega} \\ \mathbf{v} \end{pmatrix} \in \mathbb{R}^6$$

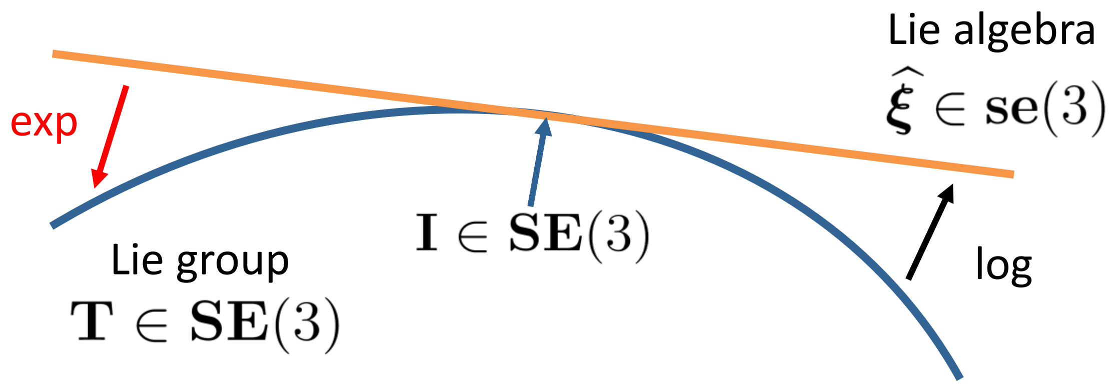
$$\boldsymbol{\omega} \in \mathbb{R}^3$$

$$\mathbf{v} \in \mathbb{R}^3$$

$$\widehat{\boldsymbol{\xi}} := \begin{pmatrix} \widehat{\boldsymbol{\omega}} & \mathbf{v} \\ \mathbf{0} & 0 \end{pmatrix} \in \mathbb{R}^{4\times 4}$$

- $\mathbf{SE}(3)$ is a smooth manifold, i.e. a Lie group
- Its Lie algebra $\mathbf{se}(3)$ provides an elegant way to parametrize poses for optimization
- Its elements $\widehat{\boldsymbol{\xi}} \in \mathbf{se}(3)$ form the tangent space of $\mathbf{SE}(3)$ at identity
- The $\mathbf{se}(3)$ elements can be interpreted as rotational and translational velocities (twists)

Recap: Exponential Map of SE(3)

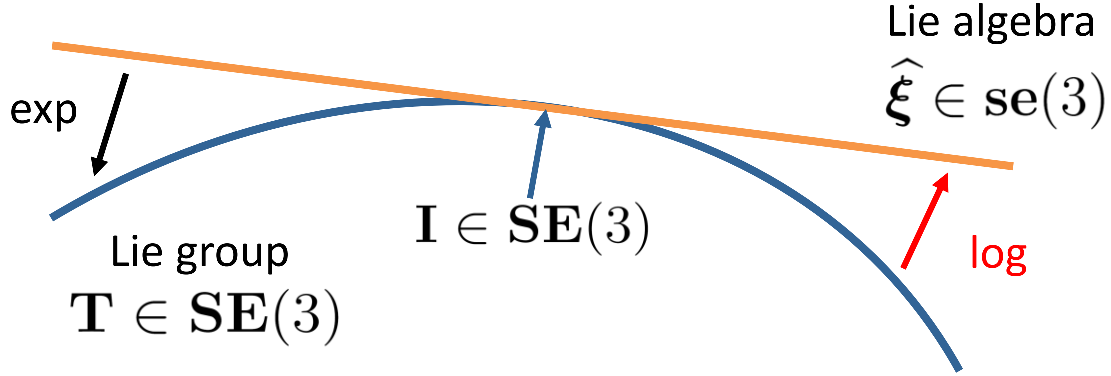

Lie algebra
$\widehat{\boldsymbol{\xi}} \in \mathbf{se}(3)$
exp
$\mathbf{I} \in \mathbf{SE}(3)$
log
Lie group
$\mathbf{T} \in \mathbf{SE}(3)$

- The exponential map finds the transformation matrix for a twist:

$$\exp\left(\widehat{\boldsymbol{\xi}}\right) = \begin{pmatrix} \exp\left(\widehat{\boldsymbol{\omega}}\right) & \mathbf{A}\mathbf{v} \\ \mathbf{0} & 1 \end{pmatrix}$$

$$\exp\left(\widehat{\boldsymbol{\omega}}\right) = \mathbf{I} + \frac{\sin|\omega|}{|\omega|}\widehat{\boldsymbol{\omega}} + \frac{1-\cos|\omega|}{|\omega|^2}\widehat{\boldsymbol{\omega}}^2 \qquad \mathbf{A} = \mathbf{I} + \frac{1-\cos|\omega|}{|\omega|^2}\widehat{\boldsymbol{\omega}} + \frac{|\omega|-\sin|\omega|}{|\omega|^3}\widehat{\boldsymbol{\omega}}^2$$

Recap: Logarithm Map of SE(3)


Lie algebra
$\widehat{\boldsymbol{\xi}} \in \mathbf{se}(3)$
exp
$\mathbf{I} \in \mathbf{SE}(3)$
log
Lie group
$\mathbf{T} \in \mathbf{SE}(3)$

- The logarithm maps twists to transformation matrices:

$$\log(\mathbf{T}) = \begin{pmatrix} \log(\mathbf{R}) & \mathbf{A}^{-1}\mathbf{t} \\ \mathbf{0} & 0 \end{pmatrix}$$

$$\log(\mathbf{R}) = \frac{|\omega|}{2\sin|\omega|}\left(\mathbf{R} - \mathbf{R}^T\right) \qquad |\omega| = \cos^{-1}\left(\frac{\operatorname{tr}(\mathbf{R}) - 1}{2}\right)$$

Recap: Some Notation for Twist Coordinates

- Let's define the following notation:
  - Inv. of hat operator: $\begin{pmatrix} 0 & -\omega_3 & \omega_2 & v_1 \\ \omega_3 & 0 & -\omega_1 & v_2 \\ -\omega_2 & \omega_1 & 0 & v_3 \\ 0 & 0 & 0 & 0 \end{pmatrix}^\vee = \left(\omega_1\ \omega_2\ \omega_3\ v_1\ v_2\ v_3\right)^\top$
  - Conversion: $\boldsymbol{\xi}\left(\mathbf{T}\right) = \left(\log(\mathbf{T})\right)^\vee \qquad \mathbf{T}\left(\boldsymbol{\xi}\right) = \exp(\widehat{\boldsymbol{\xi}})$
  - Pose inversion: $\boldsymbol{\xi}^{-1} = \log(\mathbf{T}\left(\boldsymbol{\xi}\right)^{-1})^\vee = -\boldsymbol{\xi}$
  - Pose concatenation: $\boldsymbol{\xi}_1 \oplus \boldsymbol{\xi}_2 = \left(\log\left(\mathbf{T}\left(\boldsymbol{\xi}_2\right)\mathbf{T}\left(\boldsymbol{\xi}_1\right)\right)\right)^\vee$
  - Pose difference: $\boldsymbol{\xi}_1 \ominus \boldsymbol{\xi}_2 = \left(\log\left(\mathbf{T}\left(\boldsymbol{\xi}_2\right)^{-1}\mathbf{T}\left(\boldsymbol{\xi}_1\right)\right)\right)^\vee$

Optimization with Twist Coordinates

- Twists provide a minimal local representation without singularities

- Since $\mathbf{SE}(3)$ a smooth manifold, we can decompose transformations in each optimization step into the transformation itself and an infinitesimal increment

$$\mathbf{T}(\boldsymbol{\xi}) = \mathbf{T}(\boldsymbol{\xi}) \exp\left(\widehat{\boldsymbol{\delta\xi}}\right) = \mathbf{T}(\boldsymbol{\delta\xi} \oplus \boldsymbol{\xi})$$

But!

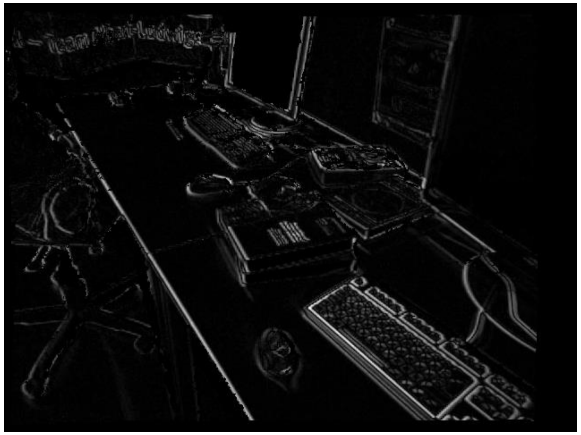
$$\mathbf{T}(\boldsymbol{\xi} + \boldsymbol{\delta\xi}) \neq \mathbf{T}(\boldsymbol{\xi})\,\mathbf{T}(\boldsymbol{\delta\xi})$$

- Example: Gradient descent on the auxiliary variable

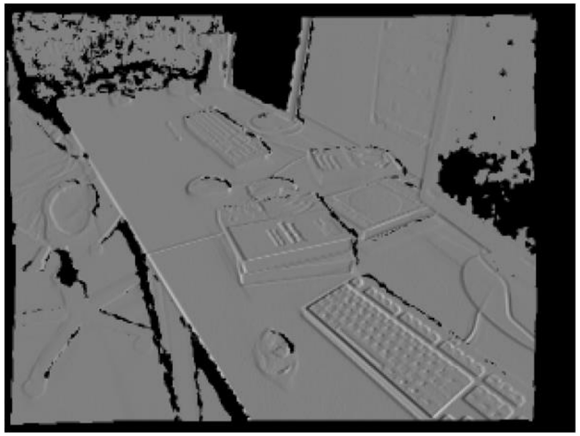
$$\boldsymbol{\delta\xi}^* = \mathbf{0} - \eta \nabla_{\boldsymbol{\delta\xi}} E(\boldsymbol{\xi}_i, \boldsymbol{\delta\xi})$$

$$\mathbf{T}(\boldsymbol{\xi}_{i+1}) = \mathbf{T}(\boldsymbol{\xi}_i) \exp\left(\widehat{\boldsymbol{\delta\xi}^*}\right)$$

Properties of Residual Linearization



I_1 - I_2



$$\left.\frac{\partial I_2\left(\pi\left(\mathbf{T}(\boldsymbol{\xi})Z_1(\mathbf{y})\overline{\mathbf{y}}\right)\right)}{\partial v_x}\right|_{\boldsymbol{\xi}=\mathbf{0}}$$

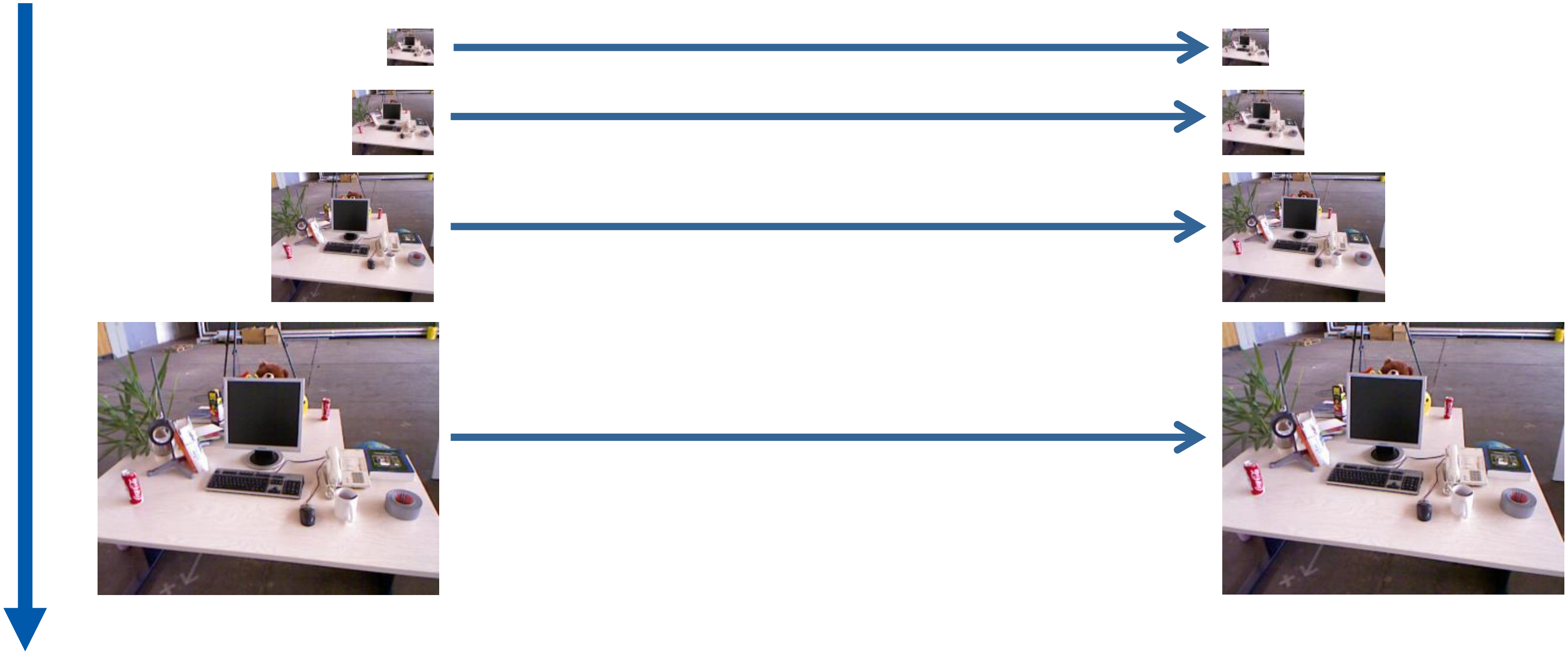
- Linearizing residuals yields

$$\nabla_{\boldsymbol{\xi}} r(\mathbf{y},\boldsymbol{\xi}) = -\nabla_\pi I_2\left(\omega(\mathbf{y},\boldsymbol{\xi})\right)\,\nabla_{\boldsymbol{\xi}}\omega(\mathbf{y},\boldsymbol{\xi})$$

  with $\omega(\mathbf{y},\boldsymbol{\xi}) := \pi(\mathbf{T}(\boldsymbol{\xi})Z_1(\mathbf{y})\overline{\mathbf{y}})$

- Linearization is only valid for motions that change the projection in a small image neighborhood that is captured by the local gradient

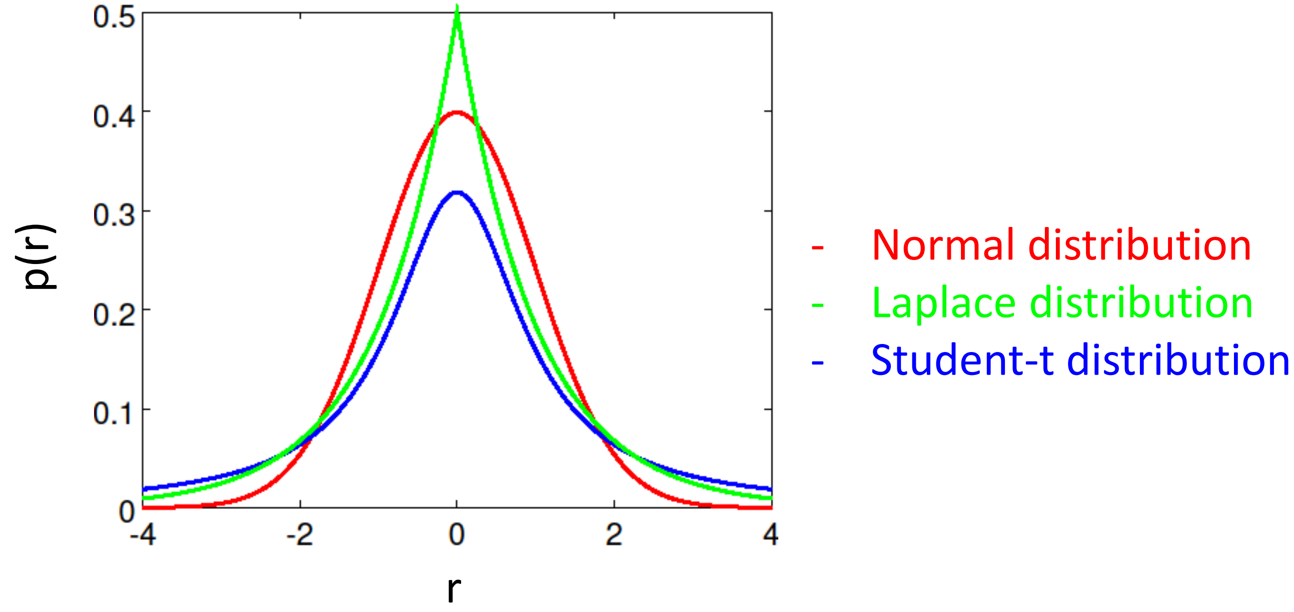
Coarse-To-Fine Optimization



coarse motion

fine motion

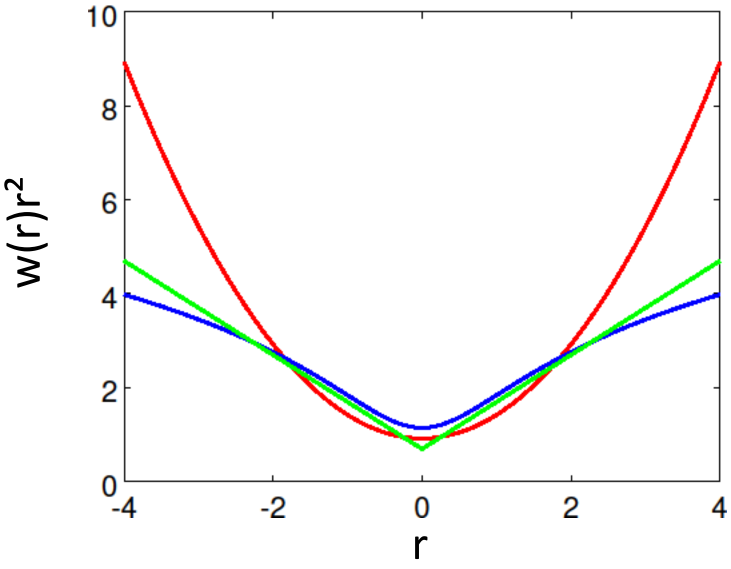
Residual Distributions



- Gaussian noise assumption on photometric residuals oversimplifies
- Outliers (occlusions, motion, etc.):
  Residuals are distributed with more mass on the larger values

Images from Kerl et al., ICRA 2013

Optimizing Non-Gaussian Measurement Noise



- Normal distribution
- Laplace distribution
- Student-t distribution

- Can we change the residual distribution in least squares optimization?
- For specific types of distributions: yes!
- Iteratively reweighted least squares: Reweight residuals in each iteration

$$E(\boldsymbol{\xi}) = \sum_{\mathbf{y} \in \Omega} w\left(r(\mathbf{y}, \boldsymbol{\xi})\right) \frac{r(\mathbf{y}, \boldsymbol{\xi})^2}{\sigma_I^2}$$

Laplace distribution:

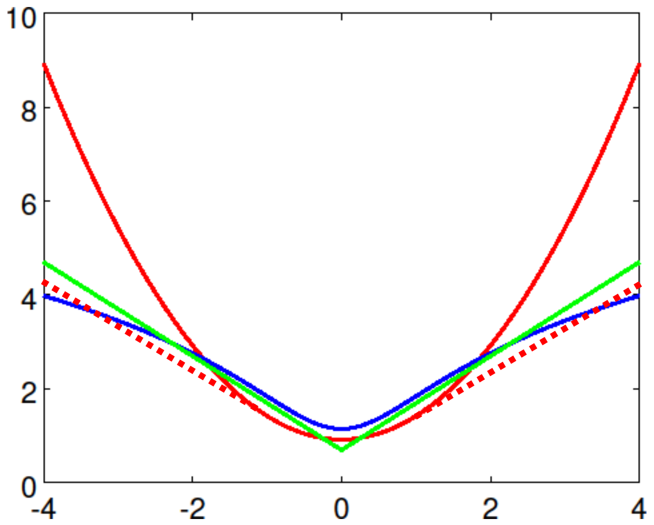
$$w\left(r(\mathbf{y}, \boldsymbol{\xi})\right) = \left| r(\mathbf{y}, \boldsymbol{\xi}) \right|^{-1}$$

- Keep weights constant in each Gauss-Newton iteration

Huber Loss

- Huber-loss „switches“ between Gaussian (locally at mean) and Laplace distribution

$$\|r\|_\delta = \begin{cases} \frac{1}{2}\|r\|_2^2 & \text{if } \|r\|_2 \le \delta \\ \delta\left(\|r\|_1 - \frac{1}{2}\delta\right) & \text{otherwise} \end{cases}$$



- Normal distribution
- Laplace distribution
- Student-t distribution

⋯⋯ Huber-loss for δ = 1

Efficient Non-Linear Least Squares

- Gauss-Newton / Levenberg-Marquardt can be applied very efficiently to direct image alignment:
  - $\mathbf{H}_i$ is only a 6x6 matrix
  - $\mathbf{b}_i = \mathbf{J}_i^\top \mathbf{W} \mathbf{r}(\boldsymbol{\xi}_i)$ is a 6x1 vector
  - Since we treat each pixel stochastically independent from neighboring pixels, $\mathbf{H}_i$ and $\mathbf{b}_i$ are summed over individual pixels

$$\mathbf{H}_i = \sum_{\mathbf{y} \in \Omega} \frac{w(\mathbf{y}, \boldsymbol{\xi}_i)}{\sigma_I^2} \mathbf{J}_{i,\mathbf{y}}^\top \mathbf{J}_{i,\mathbf{y}} \qquad \mathbf{b}_i = \sum_{\mathbf{y} \in \Omega} \mathbf{J}_{i,\mathbf{y}}^\top \frac{w(\mathbf{y}, \boldsymbol{\xi}_i)}{\sigma_I^2} r(\mathbf{y}, \boldsymbol{\xi}_i)$$

$$\mathbf{J}_{i,\mathbf{y}} := \nabla_{\delta\boldsymbol{\xi}} r(\mathbf{y}, \boldsymbol{\delta\xi} \oplus \boldsymbol{\xi}_i)$$

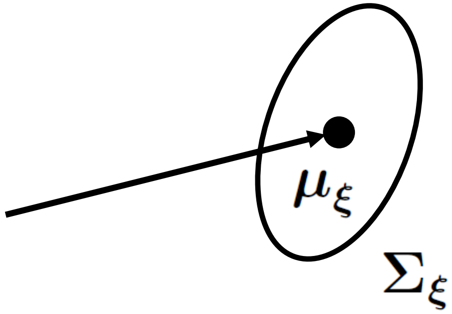
  - This allows for highly efficient parallel processing, e.g. using a GPU

Distribution of the Pose Estimate

- Non-linear least squares determines a Gaussian estimate

$$p(\boldsymbol{\xi} \mid I_1, I_2) = \mathcal{N}\left(\boldsymbol{\mu}_\xi, \boldsymbol{\Sigma}_\xi\right)$$

$$\boldsymbol{\Sigma}_\xi = \left(\nabla_\xi \mathbf{r}\left(\boldsymbol{\xi}\right)^\top \mathbf{W} \nabla_\xi \mathbf{r}\left(\boldsymbol{\xi}\right)\right)^{-1}$$



- Due to right-multiplication of pose increment $\boldsymbol{\delta\xi}$, covariance from Hessian is expressed in camera frame of I_1
- Pose covariance in frame of I_2 can be obtained using the adjoint in $\mathbf{SE}(3)$

$$p(\boldsymbol{\xi} \mid I_1, I_2) = \mathcal{N}\left(\boldsymbol{\mu}_\xi, \mathrm{ad}_{\mathbf{T}(\boldsymbol{\xi})}\, \boldsymbol{\Sigma}_{\delta\xi}\, \mathrm{ad}_{\mathbf{T}(\boldsymbol{\xi})}^\top\right)$$

$$\boldsymbol{\Sigma}_{\delta\xi} = \left(\nabla_{\delta\xi} \mathbf{r}\left(\boldsymbol{\delta\xi}, \boldsymbol{\xi}\right)^\top \mathbf{W} \nabla_{\delta\xi} \mathbf{r}\left(\boldsymbol{\delta\xi}, \boldsymbol{\xi}\right)\right)^{-1}$$

$$\mathrm{ad}_{\mathbf{T}(\boldsymbol{\xi})} = \begin{pmatrix} \mathbf{R}(\boldsymbol{\xi}) & \mathbf{0} \\ \widehat{\boldsymbol{t}}\mathbf{R}(\boldsymbol{\xi}) & \mathbf{R}(\boldsymbol{\xi}) \end{pmatrix}$$

Algorithm: Direct RGB-D Visual Odometry

Input: RGB-D image sequence $I_{0:t}, Z_{0:t}$

Output: aggregated camera poses $\mathbf{T}_{0:t}$

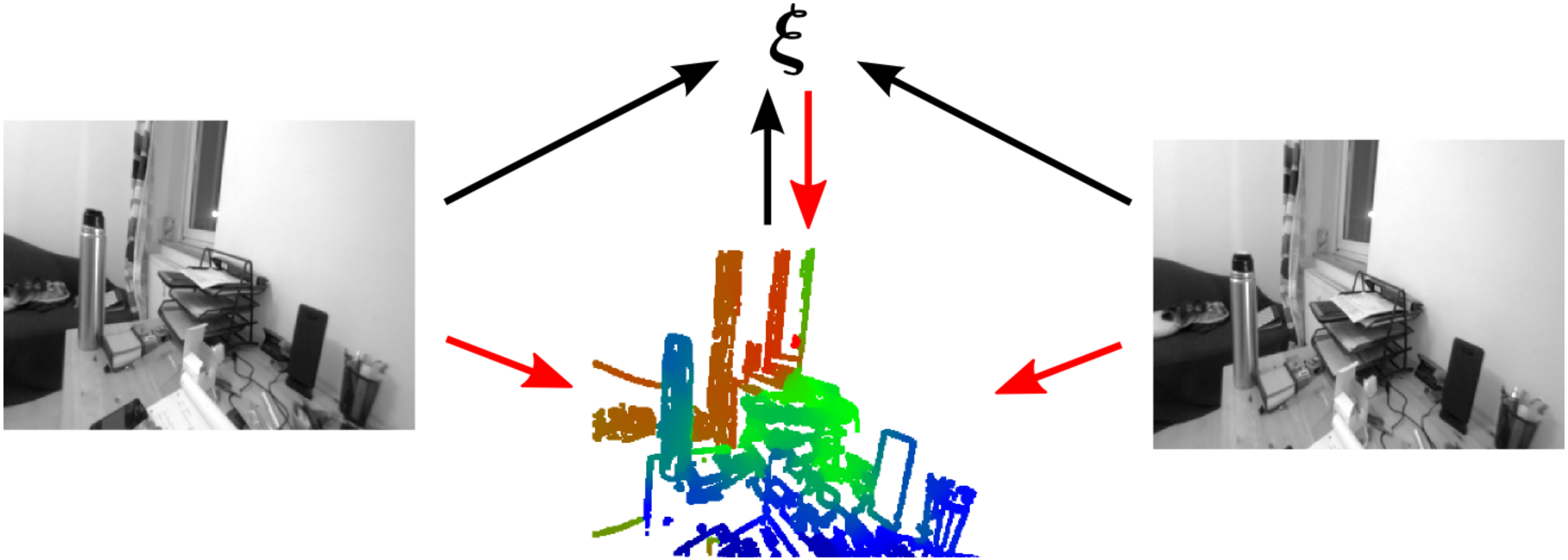
Algorithm:

For each current RGB-D image I_k, Z_k :

1. Estimate relative camera motion $\mathbf{T}_k^{k-1}$ towards the previous RGB-D frame using direct image alignment $\mathbf{T}_k = \mathbf{T}_{k-1}\mathbf{T}_k^{k-1}$
2. Concatenate estimated camera motion with previous frame camera pose to obtain current camera pose estimate

Monocular Direct Visual Odometry

- Estimate motion and depth concurrently

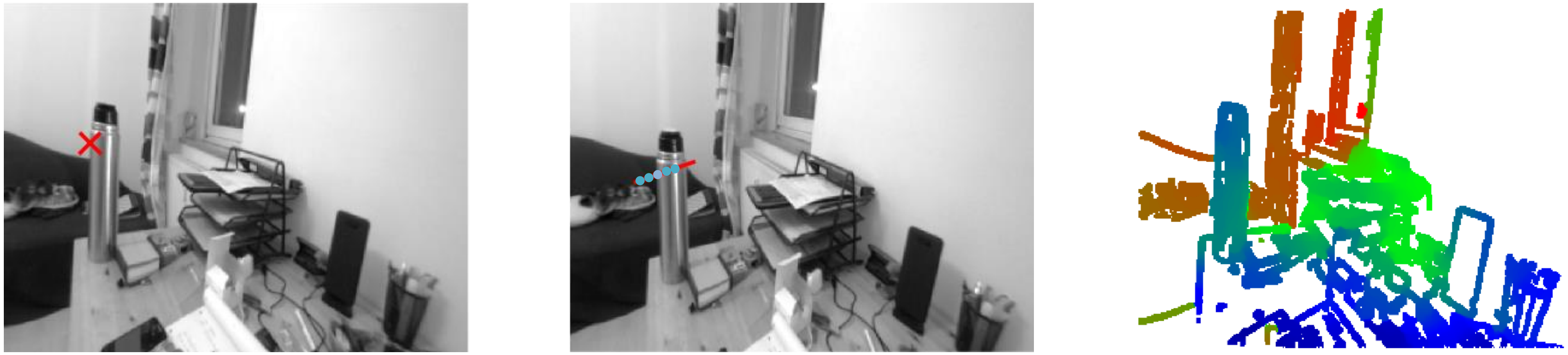


- Alternating optimization: **Tracking** and **Mapping**

Images from: Engel et al., ICCV 2013

Semi-Dense Mapping

- Estimate inverse depth and variance at high gradient pixels
- Correspondence search along epipolar line (5-pixel intensity SSD)

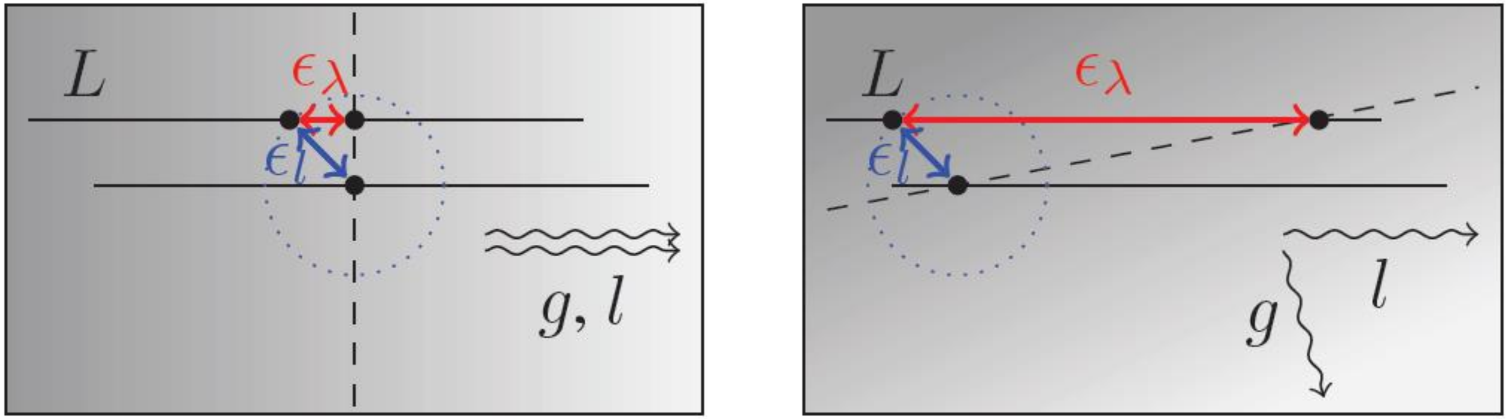


- Kalman-filtering of depth map:
  - Propagate depth map & variance from previous frame
  - Update depth map & variance with new depth observations

Images from: Engel et al., ICCV 2013

Semi-Dense Mapping

- Estimate for inverse depth uncertainty from geometric and intensity noise



Geometric noise

$$\sigma^2_{\lambda(\xi,\pi)} = \frac{\sigma_l^2}{\langle g, l \rangle^2}$$

pos. variance of epipolar line

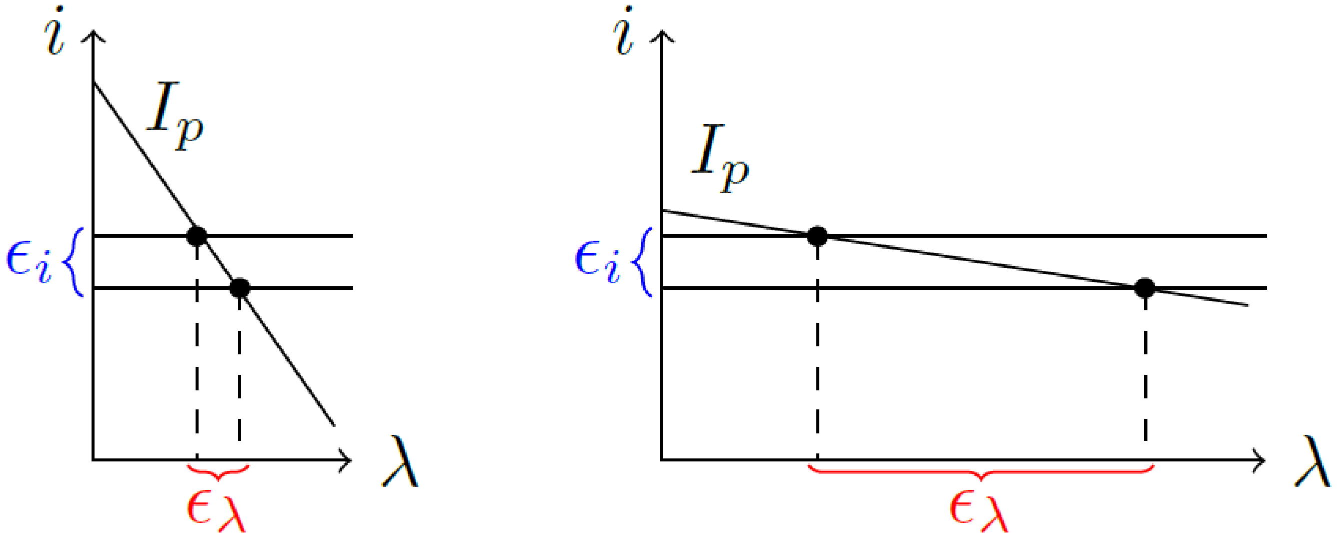
gradient direction

epipolar line direction

Images from: Engel et al., ICCV 2013

Semi-Dense Mapping

- Estimate for inverse depth uncertainty from geometric and intensity noise



Intensity noise

$$\sigma^2_{\lambda(I)} = \frac{2\sigma_i^2}{g_p^2}$$

intensity noise variance

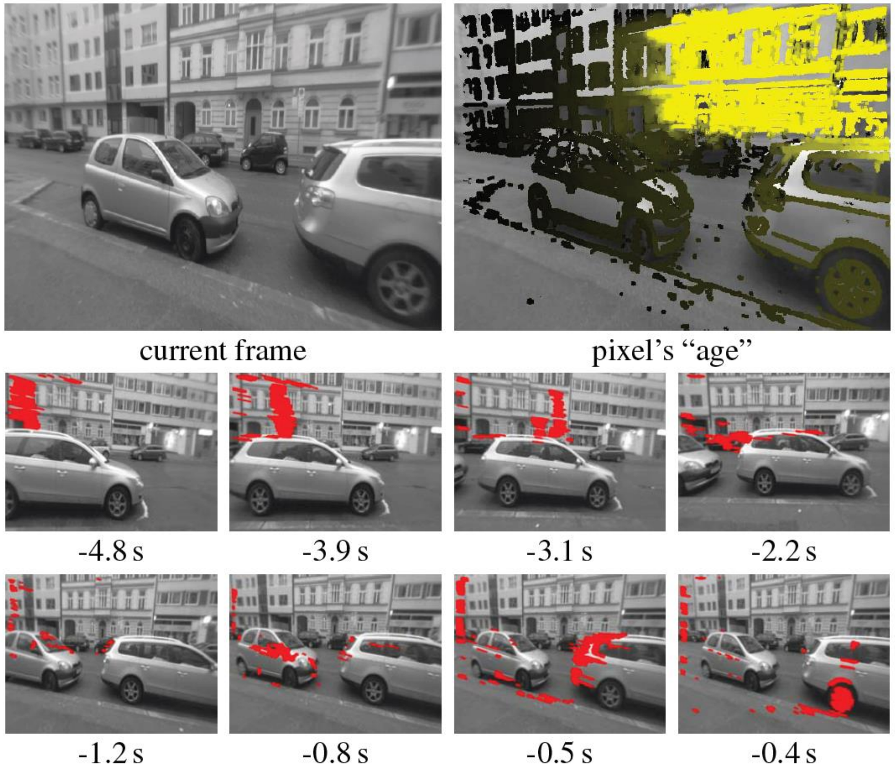
image gradient magnitude at epipolar line

Images from: Engel et al., ICCV 2013

Choosing the Stereo Reference Frame

- Naive: use one specific reference frame (f.e. the previous frame or a keyframe)

- We can also select the reference frame for stereo comparisons for each pixel individually in order to achieve a trade-off between accuracy and computation time



current frame

pixel's "age"

-4.8 s

-3.9 s

-3.1 s

-2.2 s

-1.2 s

-0.8 s

-0.5 s

-0.4 s

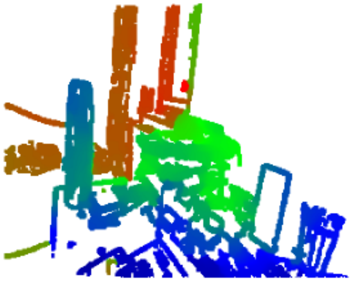
Heuristics from Engel et al., ICCV 2013:
Use oldest frame in which pixel still visible but disparity search range and observation angle below threshold

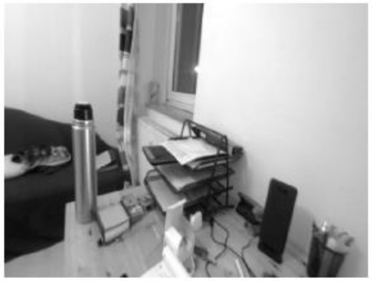
Images from: Engel et al., ICCV 2013

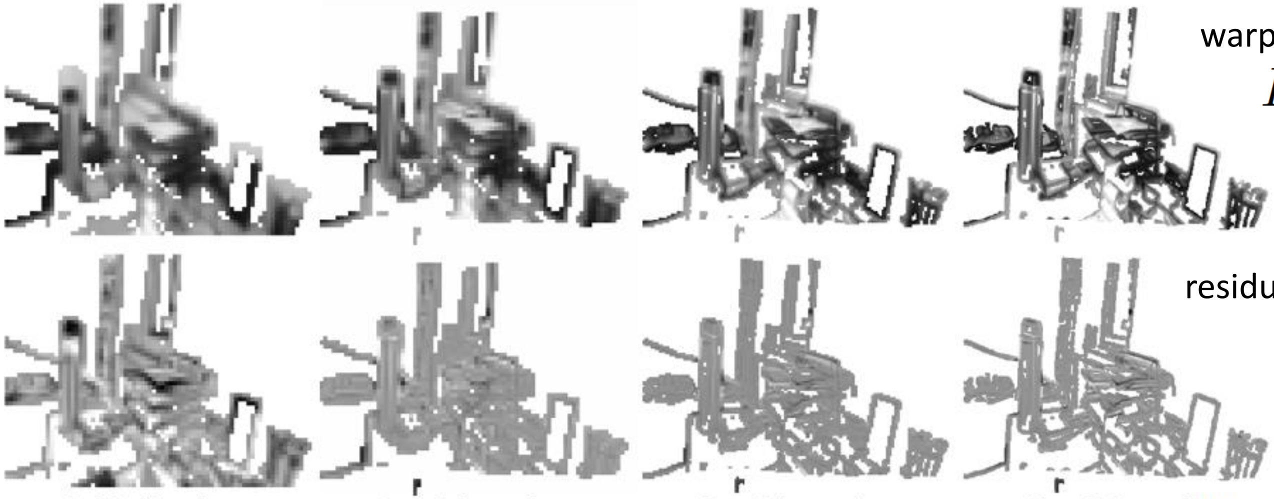
Semi-Dense Direct Image Alignment

$$E(\boldsymbol{\xi}) = \sum_{\mathbf{y}\in\Omega^Z} w\left(r(\mathbf{y},\boldsymbol{\xi})\right) \frac{r(\mathbf{y},\boldsymbol{\xi})^2}{\sigma^2_{Z(\mathbf{y})}}$$

$$r(\mathbf{y},\boldsymbol{\xi}) = I_1\left(\mathbf{y}\right) - I_2\left(\pi\left(\mathbf{T}(\boldsymbol{\xi})Z_1(\mathbf{y})\bar{\mathbf{y}}\right)\right)$$







initialization on lvl 3 (80×60)

after 8 iterations on lvl 3 (80×60)

after 3 iterations on lvl 2 (160×120)

after 3 iterations on lvl 1 (320×240)

Images from: Engel et al., ICCV 2013

Algorithm: Direct Monocular Visual Odometry

Input: Monocular image sequence $I_{0:t}$
Output: aggregated camera poses $\mathbf{T}_{0:t}$

Algorithm:

Initialize depth map Z_0 f.e. from first two frames with a point-based method

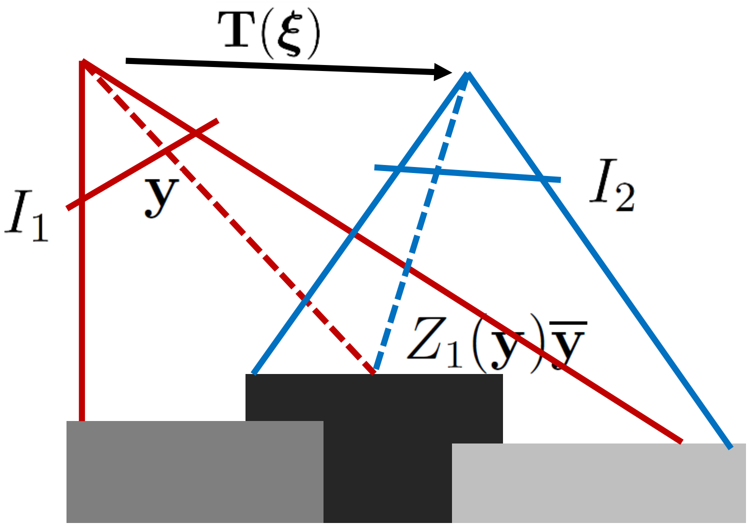
For each current image I_k:

1. Estimate relative camera motion $\mathbf{T}_k^{k-1}$ towards the previous image with estimated semi-dense depth map Z_{k-1} using direct image alignment
2. Concatenate estimated camera motion with previous frame camera pose to obtain current camera pose estimate $\mathbf{T}_k = \mathbf{T}_{k-1}\mathbf{T}_k^{k-1}$
3. Propagate semi-dense depth map Z_{k-1} from previous frame to current frame to obtain $\widetilde{Z}_k$
4. Update propagated semi-dense depth map $\widetilde{Z}_k$ with temporal stereo depth measurements to obtain Z_k

Direct Visual Odometry Example (Monocular)

Engel et al., Semi-Dense Visual Odometry for a Monocular Camera, ICCV 2013

Direct Image Alignment Revisited


$\mathbf{T}(\boldsymbol{\xi})$
I_1
$\mathbf{y}$
I_2
$Z_1(\mathbf{y})\overline{\mathbf{y}}$

- If we know pixel depth, we can „simulate“ an image from a different view point
- Ideally, the warped image is the same as the image taken from that pose:

$$I_1(\mathbf{y}) = I_2\left(\pi\left(\mathbf{T}(\boldsymbol{\xi}) Z_1(\mathbf{y})\overline{\mathbf{y}}\right)\right)$$

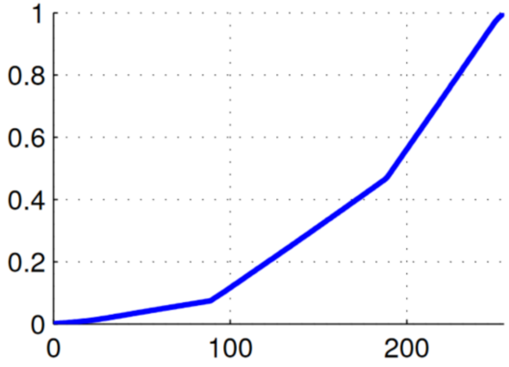
- What do we mean with „ideally“ ?

Recap: Camera Response Function

- The objects in the scene radiate light which is focused by the lens onto the image sensor

- The pixels of the sensor observe an irradiance $B : \Omega \to \mathbb{R}$ for an exposure time t

example inv. G



- The camera electronics translates the accumulated irradiance into intensity values according to a non-linear camera response function $G : \mathbb{R} \to [0, 255]$

- The measured intensity is $I(\mathbf{x}) = G(tB(\mathbf{x}))$

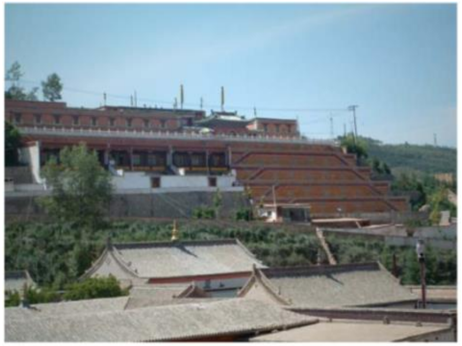
Recap: Vignetting

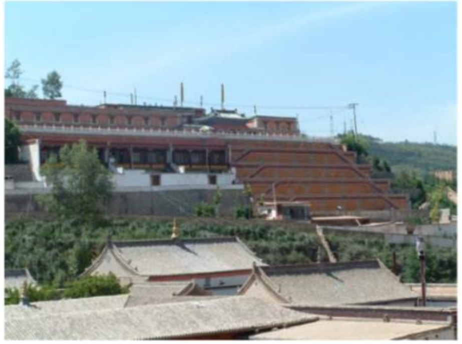
- Lenses gradually focus more light at the center of the image than at the image borders
- The image appears darker towards the borders
- Also called “lens attenuation”
- Lense vignetting can be modelled as a map $V : \Omega \rightarrow [0, 1]$

- Intensity measurement model

$$I(\mathbf{x}) = G(tV(\mathbf{x})B(\mathbf{x}))$$

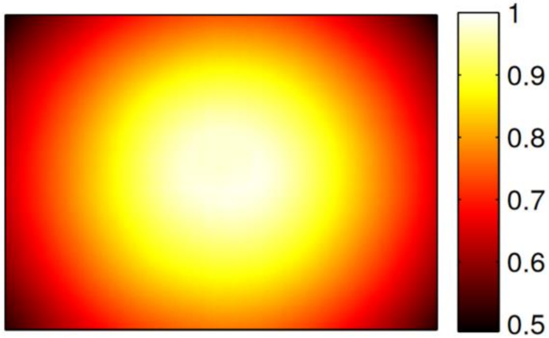
uncorrected





corrected

$V(\mathbf{x})$



Brightness Constancy Assumption Revisited

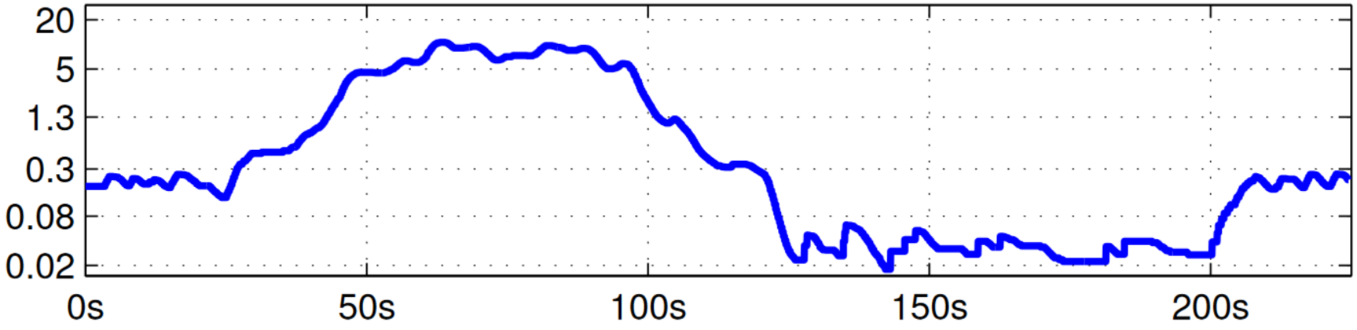
- Camera images include vignetting effects and non-linear camera response function

- Idea: invert vignetting and camera response function using a known calibration

- Perform direct image alignment on irradiance images:

$$I'(\mathbf{y}) = tB(\mathbf{y}) = \frac{G^{-1}(I(\mathbf{y}))}{V(\mathbf{y})}$$

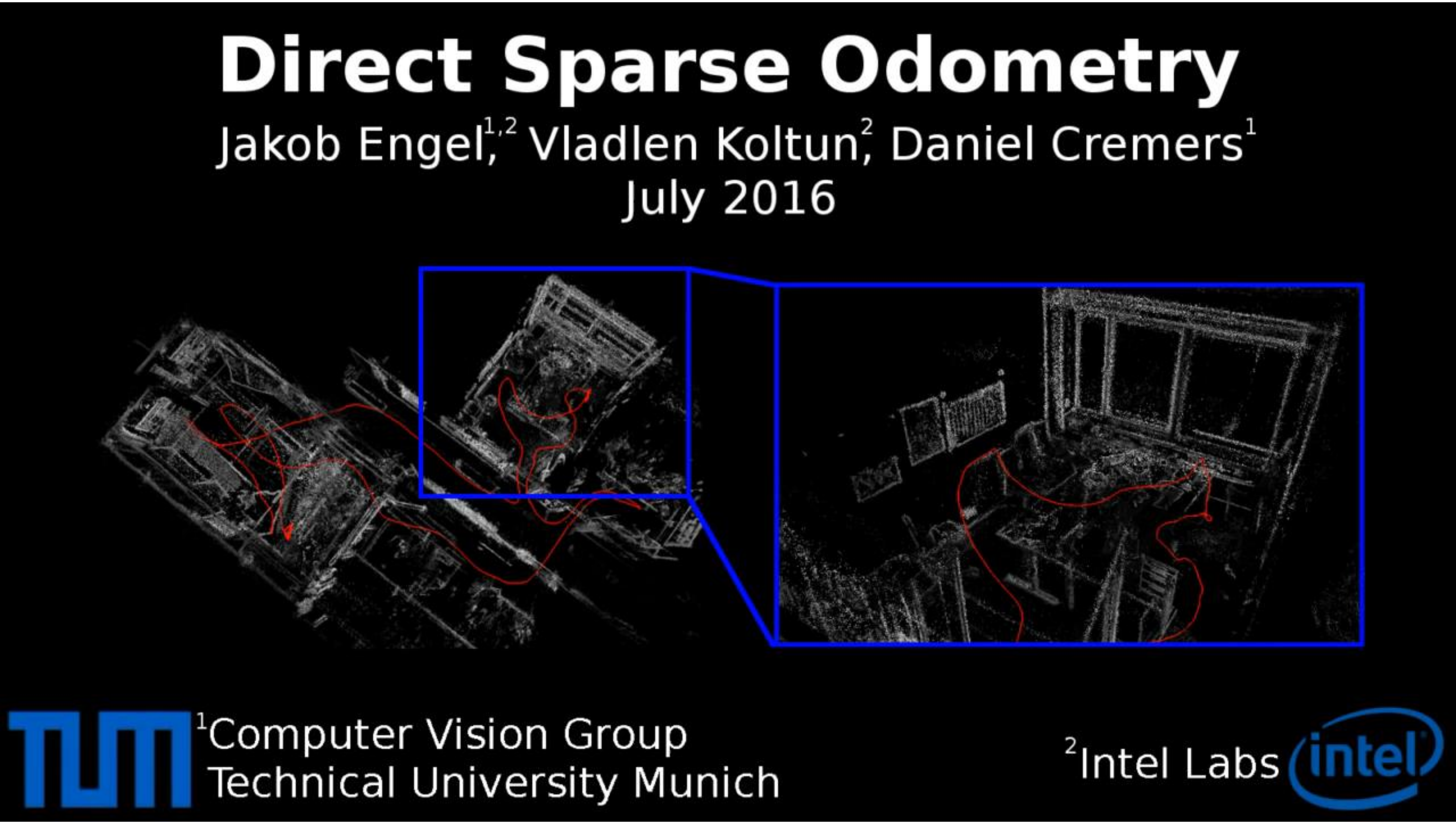
Brightness Constancy Assumption Revisited



- Automatic exposure adjustment needed in realistic environments
- Add exposure parameters explicitly to objective function:

$$\left(I_2(\omega(\mathbf{y}, \boldsymbol{\xi}, Z_1(\mathbf{y}))) - b_2\right) - \frac{t_2 \exp(a_2)}{t_1 \exp(a_1)}\left(I_1(\mathbf{y}) - b_1\right)$$

Direct Sparse Visual Odometry (Monocular)



Direct Sparse Odometry

Jakob Engel[1,2], Vladlen Koltun[2], Daniel Cremers[1]

July 2016

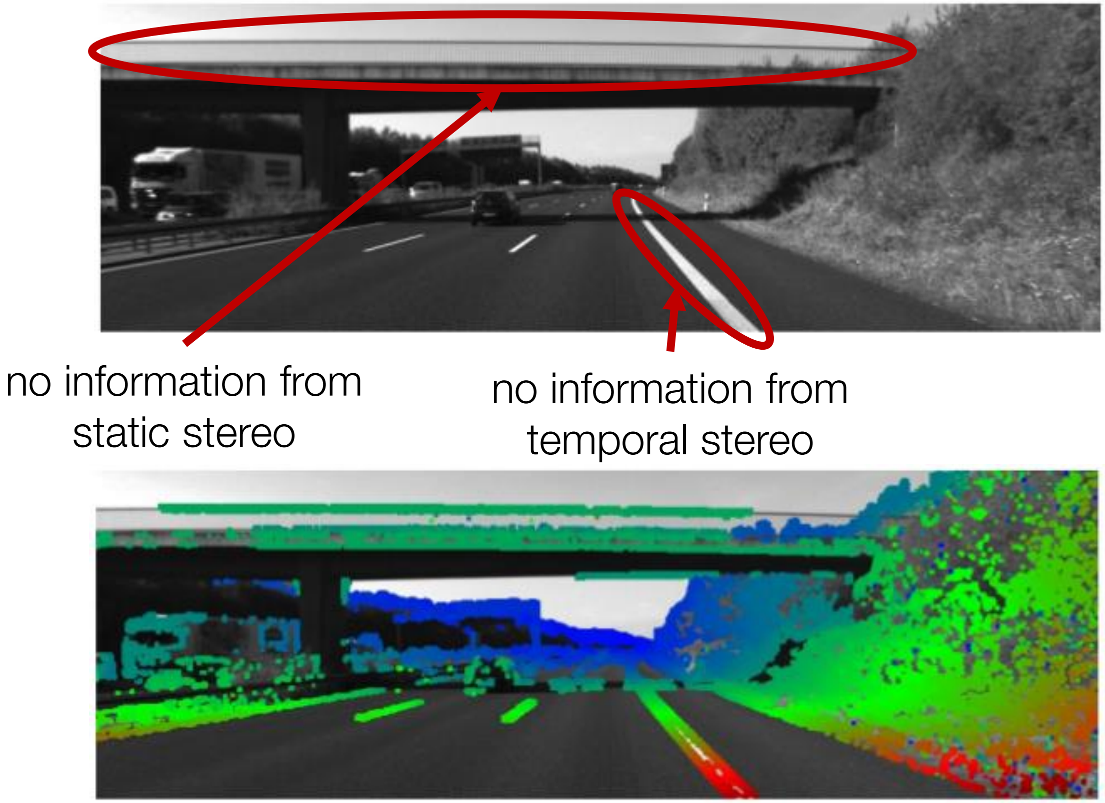
[1] Computer Vision Group
Technical University Munich

[2] Intel Labs

Engel et al., Direct Sparse Odometry, TPAMI 2017

Direct Mapping with Stereo Cameras

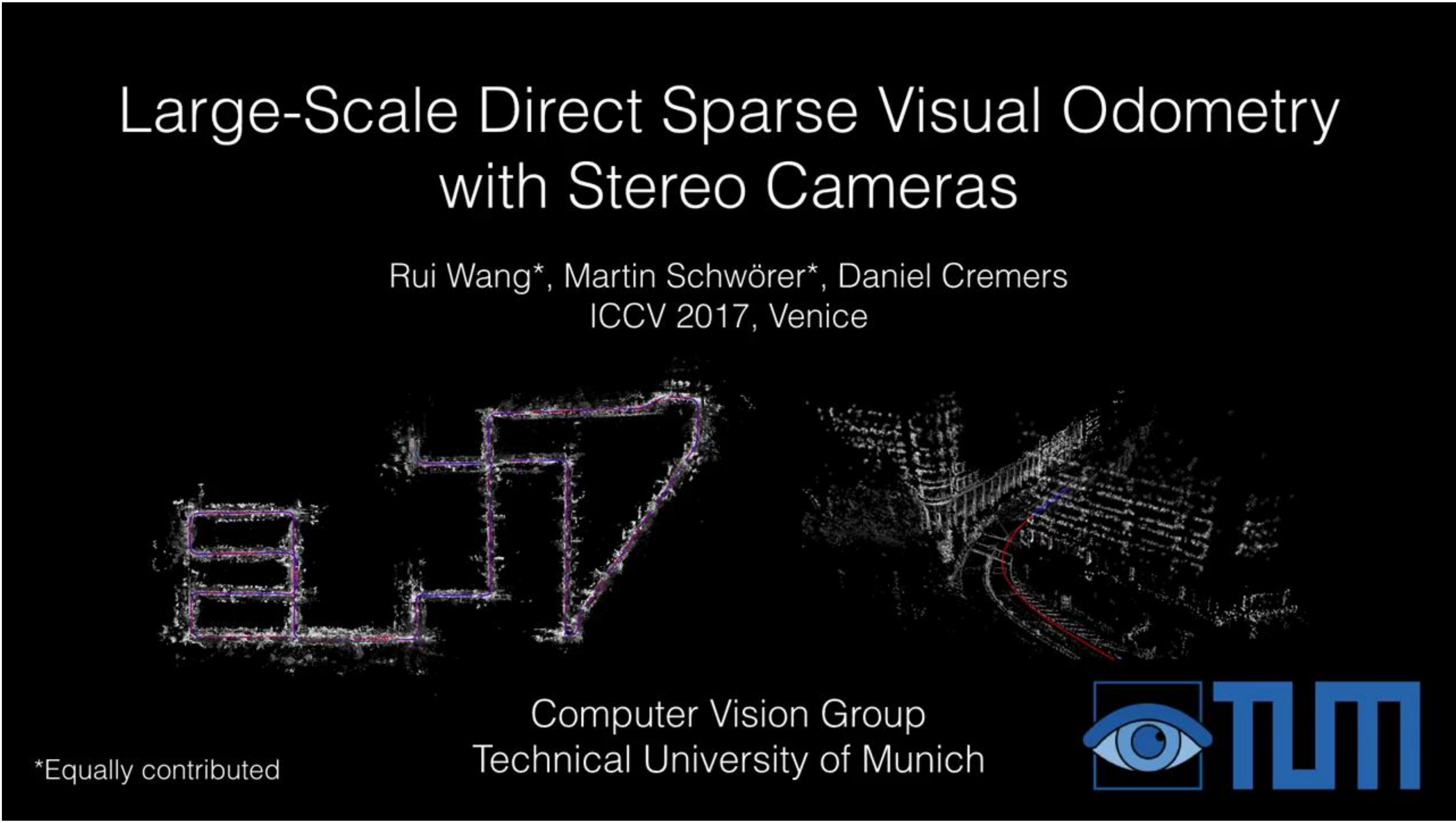
- For stereo cameras, we can exploit the known camera extrinsics to estimate depth from static stereo (left-right images) in addition to temporal stereo (successive left or right images)



no information from static stereo

no information from temporal stereo

Direct Sparse Visual Odometry (Stereo)



Large-Scale Direct Sparse Visual Odometry with Stereo Cameras

Rui Wang*, Martin Schwörer*, Daniel Cremers
ICCV 2017, Venice

Computer Vision Group
Technical University of Munich

*Equally contributed

Wang et al., Stereo DSO: Large-Scale Direct Sparse Visual Odometry with Stereo Cameras, ICCV 2017

Lessons Learned Today

- Direct image alignment avoids manually designed keypoints and can use all available image information
- Direct visual odometry
  - Dense RGB-D odometry by direct image alignment with measured depth
  - Direct image alignment for monocular cameras requires depth estimation from temporal stereo
  - Stereo cameras: Direct depth estimation using static and temporal stereo
- Direct image alignment as non-linear least squares problem
  - Linearization of the residuals requires a coarse-to-fine optimization scheme
  - SE(3) Lie algebra provides an elegant way of motion representation for gradient-based optimization
  - Iteratively reweighted least squares allows for wider set of residual distributions than Gaussians
- Photometric calibration and exposure parameter estimation

Thanks for your attention!