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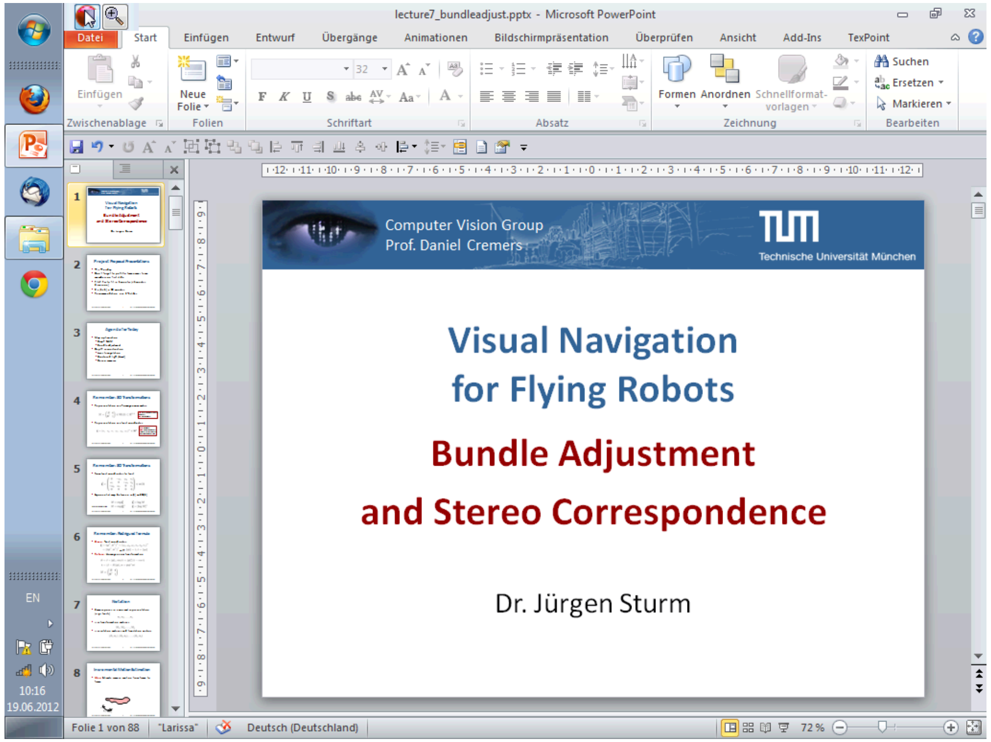
Title: Sturm: Visual Navigation (19.06.2012)

Date: Tue Jun 19 10:16:39 CEST 2012

Duration: 86:43 min

Pages: 85



Computer Vision Group
Prof. Daniel Cremers
Technische Universität München

Visual Navigation for Flying Robots

Bundle Adjustment and Stereo Correspondence

Dr. Jürgen Sturm

Project Proposal Presentations

- This Thursday
- Don't forget to put title, team name, team members on first slide
- Pitch has to fit in 5 minutes (+5 minutes discussion)
- 9 x (5+5) = 90 minutes
- Recommendation: use 3-5 slides

Agenda for Today

- Map optimization
  - Graph SLAM
  - Bundle adjustment
- Depth reconstruction
  - Laser triangulation
  - Structured light (Kinect)
  - Stereo cameras

Remember: 3D Transformations

- Representation as a homogeneous matrix

$$M = \begin{pmatrix} R & \mathbf{t} \\ \mathbf{0}^\top & 1 \end{pmatrix} \in \mathrm{SE}(3) \subset \mathbb{R}^{4\times 4}$$

Pro: easy to concatenate and invert
Con: not minimal

- Representation as a twist coordinates

$$\boldsymbol{\xi} = (v_x \quad v_y \quad v_z \quad \omega_x \quad \omega_y \quad \omega_z)^\top \in \mathbf{R}^6$$

Pro: minimal
Con: need to convert to matrix for concat-enation and inversion

Remember: 3D Transformations

- From twist coordinates to twist

$$\hat{\boldsymbol{\xi}} = \begin{pmatrix} 0 & -\omega_z & \omega_y & v_x \\ \omega_z & 0 & -\omega_x & v_y \\ -\omega_y & \omega_x & 0 & v_z \\ 0 & 0 & 0 & 0 \end{pmatrix} \in \mathrm{se}(3)$$

- Exponential map between se(3) and SE(3)

$$M = \exp \hat{\boldsymbol{\xi}} \qquad \hat{\boldsymbol{\xi}} = \log M$$

alternative notation: $M = \exp[\boldsymbol{\xi}]^\wedge \qquad \boldsymbol{\xi} = [\log M]^\vee$

Remember: Rodrigues' formula

- **Given:** Twist coordinates

$$\boldsymbol{\xi} = (\boldsymbol{\omega}^\top, \boldsymbol{v}^\top)^\top = (\omega_x, \omega_y, \omega_z, v_x, v_y, v_z)^\top$$
$$= (t\bar{\boldsymbol{\omega}}^\top, \boldsymbol{v}^\top)^\top \text{ with } \|\bar{\boldsymbol{\omega}}\| = 1, t = \|\boldsymbol{\omega}\|$$

- **Return:** Homogeneous transformation

$$R = I + [\bar{\boldsymbol{\omega}}]_\times \sin(t) + [\bar{\boldsymbol{\omega}}]_\times^2 (1 - \cos t)$$
$$\mathbf{t} = (I - R)[\bar{\boldsymbol{\omega}}]_\times \boldsymbol{v} + \bar{\boldsymbol{\omega}}\bar{\boldsymbol{\omega}}^\top \boldsymbol{v} t$$
$$M = \begin{pmatrix} R & \mathbf{t} \\ \mathbf{0}^\top & 1 \end{pmatrix}$$

Notation

- Camera poses in a minimal representation (e.g., twists)

$$\mathbf{c}_1, \mathbf{c}_2, \ldots, \mathbf{c}_n$$

- ... as transformation matrices

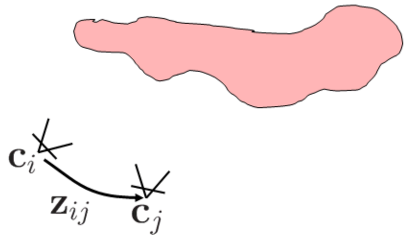
$$M_1, M_2, \ldots, M_n$$

- ... as rotation matrices and translation vectors

$$(R_1, \mathbf{t}_1), (R_2, \mathbf{t}_2), \ldots, (R_n, \mathbf{t}_n)$$

Incremental Motion Estimation

- **Idea:** Estimate camera motion from frame to frame



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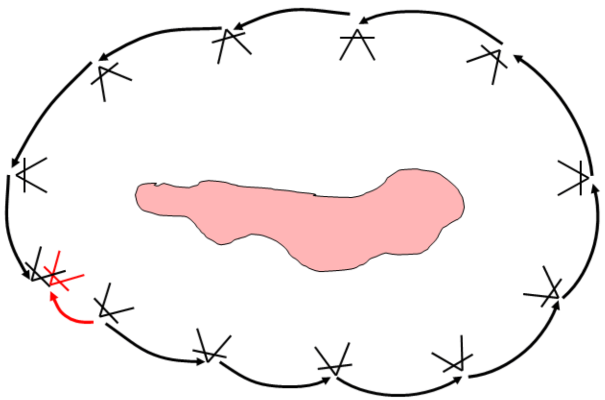
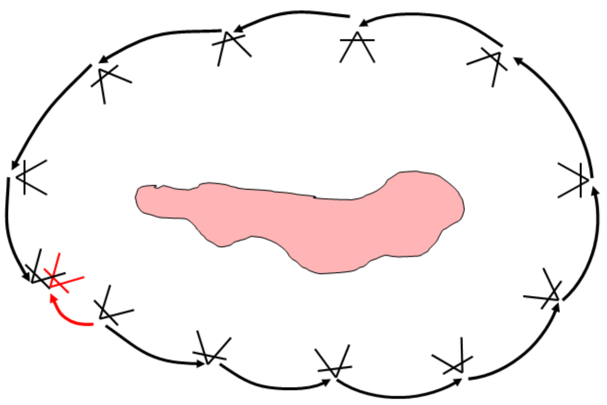


Loop Closures

- **Idea:** Estimate camera motion from frame to frame
- **Problem:**
  - Estimates are inherently noisy
  - Error accumulates over time → drift

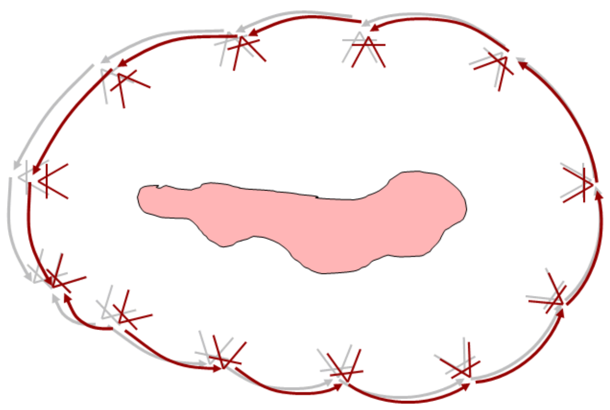
Incremental Motion Estimation

- **Idea:** Estimate camera motion from frame to frame



Loop Closures

- **Solution:** Use loop-closures to minimize the drift / minimize the error over all constraints

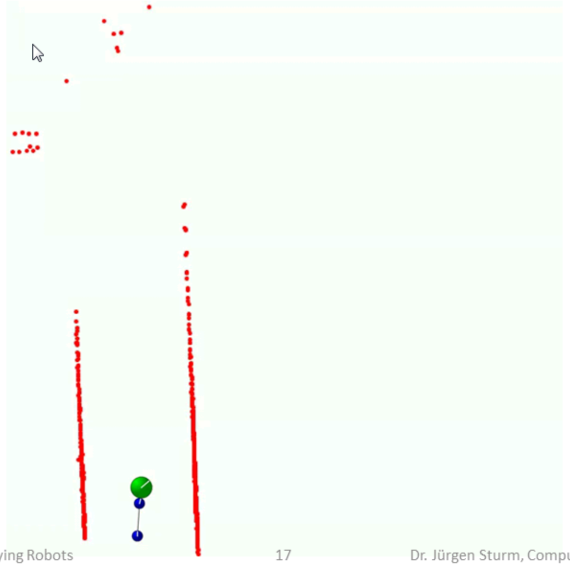


Graph SLAM

[Olson et al., 2006]

- Use a graph to represent the model
- Every **node** in the graph corresponds to a pose of the robot during mapping
- Every **edge** between two nodes corresponds to a spatial constraint between them
- **Graph-based SLAM:** Build the graph and find the robot poses that **minimize the error** introduced by the constraints

Example: Graph SLAM on Intel Dataset



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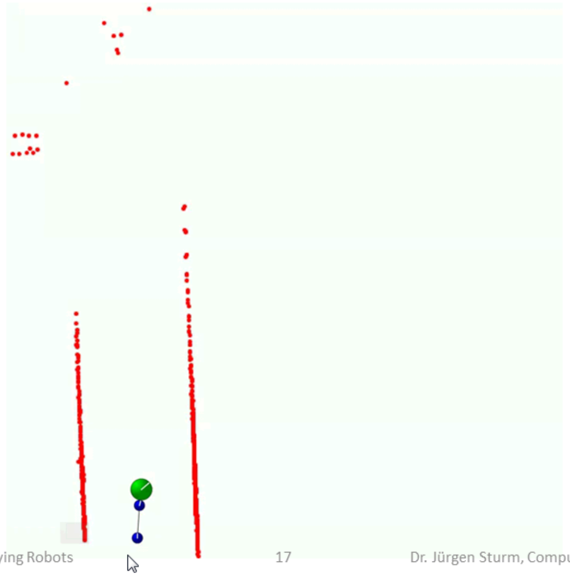
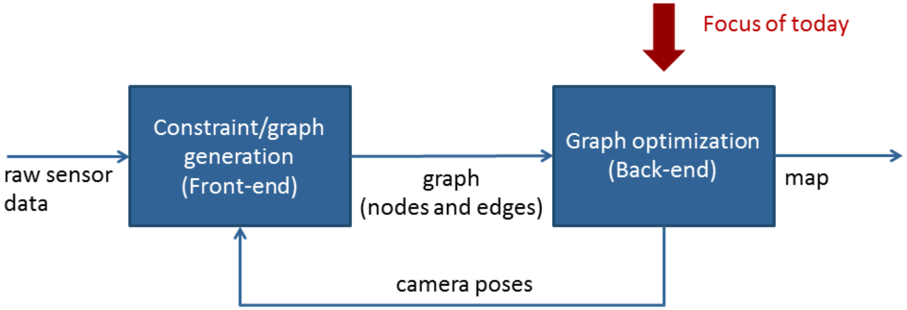


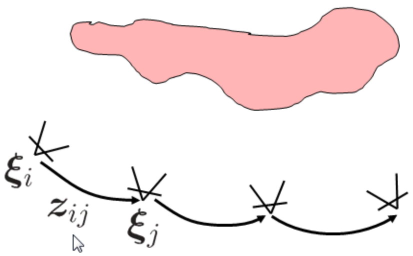
Graph SLAM Architecture



- Interleaving process of front-end and back-end
- A consistent map helps to determine new constraints by reducing the search space

Problem Definition

- **Given:** Set of observations $\mathbf{z}_{ij} \in \mathbb{R}^6$
- **Wanted:** Set of camera poses $\mathbf{c}_1, \ldots, \mathbf{c}_n \in \mathbb{R}^6$
  ➔ State vector $\mathbf{x} = (\mathbf{c}_1^\top, \ldots, \mathbf{c}_n^\top)^\top \in \mathbb{R}^{6n}$



Map Error

- Real observation $\mathbf{z}_{ij}$
- Expected observation $\bar{\mathbf{z}}_{ij} = \mathbf{c}_j \ominus \mathbf{c}_i$
- Difference between observation and expectation

$$\mathbf{e}_{ij} = \mathbf{z}_{ij} \ominus \bar{\mathbf{z}}_{ij}$$

- Given the correct map, this difference is the result of sensor noise…

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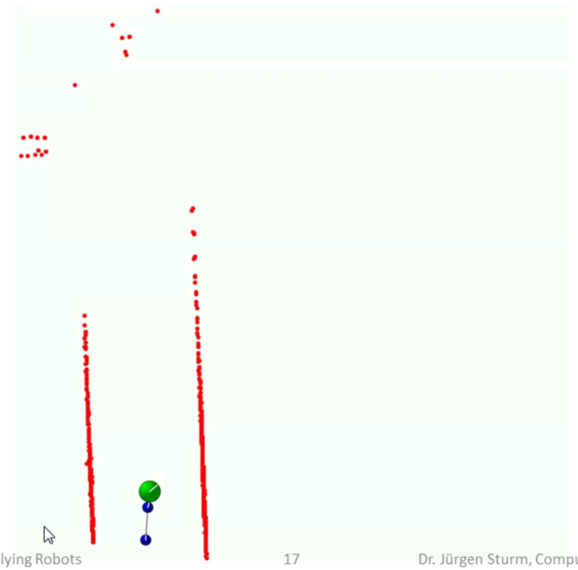

Incremental Motion Estimation

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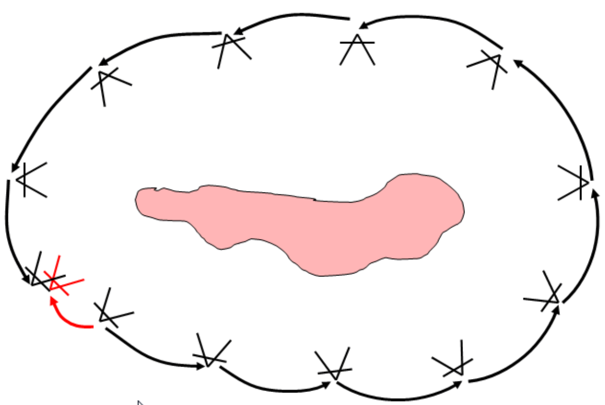

Error Function

- Map error (over all observations)

$$f(\mathbf{x}) = \sum_{ij} f_{ij}(\mathbf{x}) = \sum_{ij} \mathbf{e}_{ij}(\mathbf{x})^\top \Sigma_{ij}^{-1} \mathbf{e}_{ij}(\mathbf{x})$$

- **Minimize this error** by optimizing the camera poses

$$\mathbf{x}^* = \arg\min_{\mathbf{x}} \sum_{ij} \mathbf{e}_{ij}(\mathbf{x})^\top \Sigma_{ij}^{-1} \mathbf{e}_{ij}(\mathbf{x})$$

- How can we solve this optimization problem?

Non-Linear Minimization

Gauss-Newton Method:

1. Linearize the error function
2. Compute its derivative
3. Set the derivative to zero
4. Solve the linear system
5. Iterate this procedure until convergence

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Step 1: Linearize the Error Function

- Error function

$$f(\mathbf{x}) = \sum_{ij} f_{ij}(\mathbf{x}) = \sum_{ij} \mathbf{e}_{ij}(\mathbf{x})^\top \Sigma_{ij}^{-1} \mathbf{e}_{ij}(\mathbf{x})$$

- Evaluate the error function around the initial guess

$$f(\mathbf{x}+\Delta\mathbf{x}) = \sum_{ij} \mathbf{e}_{ij}(\mathbf{x}+\Delta\mathbf{x})^\top \Sigma_{ij}^{-1} \underline{\mathbf{e}_{ij}(\mathbf{x}+\Delta\mathbf{x})}$$

Let's derive this term first...

Linearize the Error Function

- Approximate the error function around an initial guess $\mathbf{x}$ using Taylor expansion

$$\mathbf{e}_{ij}(\mathbf{x}+\Delta\mathbf{x}) \simeq \mathbf{e}_{ij}(\mathbf{x}) + J_{ij}\Delta\mathbf{x}$$

with

$$J_{ij}(\mathbf{x}) = \left(\frac{\partial \mathbf{e}_{ij}(\mathbf{x})}{\partial \mathbf{c}_1} \quad \frac{\partial \mathbf{e}_{ij}(\mathbf{x})}{\partial \mathbf{c}_2} \quad \cdots \quad \frac{\partial \mathbf{e}_{ij}(\mathbf{x})}{\partial \mathbf{c}_n} \right)$$

Linearizing the Error Function

Linearize $f(\mathbf{x}) = \sum_{ij} \mathbf{e}_{ij}(\mathbf{x})^T \Sigma_{ij}^{-1} \mathbf{e}_{ij}(\mathbf{x})$

$$\simeq \mathbf{c} + 2\mathbf{b}^\top \Delta\mathbf{x} + \Delta\mathbf{x}^\top H \Delta\mathbf{x}$$

with $\mathbf{b}^\top = \sum_{ij} \mathbf{e}_{ij}^\top \Sigma_{ij}^{-1} J_{ij}$

$$H = \sum_{ij} J_{ij}^\top \Sigma_{ij}^{-1} J_{ij}$$

- What is the structure of $\mathbf{b}^\top$ and H? (Remember: all J_{ij}'s are sparse)

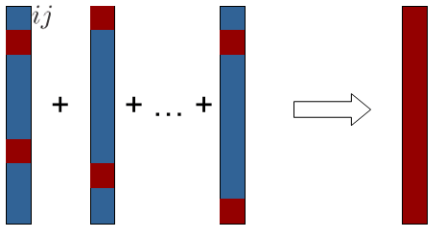
Illustration of the Structure

$$\mathbf{b}_{ij}^\top = \mathbf{e}_{ij}^\top \Sigma_{ij}^{-1} J_{ij}$$

Non-zero only at $\mathbf{c}_i$ and $\mathbf{c}_j$

Illustration of the Structure

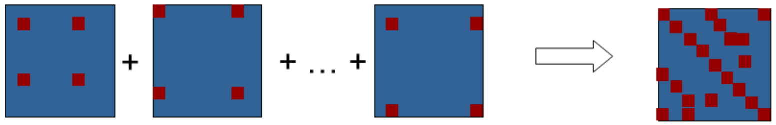
$$\mathbf{b} = \sum_{ij} \mathbf{b}_{ij}$$



b: dense vector

$$H = \sum_{ij} H_{ij}$$

H: sparse block structure with main diagonal



(Linear) Least Squares Minimization

1. Linearize error function
$$f(\mathbf{x}+\Delta\mathbf{x}) \simeq \mathbf{c} + 2\mathbf{b}^\top\Delta\mathbf{x} + \Delta\mathbf{x}^\top H \Delta\mathbf{x}$$
2. Compute the derivative
$$\frac{\mathrm{d}f(\mathbf{x}+\Delta\mathbf{x})}{\mathrm{d}\Delta\mathbf{x}} = 2\mathbf{b} + 2H\Delta\mathbf{x}$$
3. Set derivative to zero
$$H\Delta\mathbf{x} = -\mathbf{b}$$
4. Solve this linear system of equations, e.g.,
$$\Delta\mathbf{x} = -H^{-1}\mathbf{b}$$

Gauss-Newton Method

Problem: $f(\mathbf{x})$ is non-linear!

Algorithm: Repeat until convergence

1. Compute the terms of the linear system
$$\mathbf{b}^\top = \sum_{ij} \mathbf{e}_{ij}^T \Sigma_{ij}^{-1} J_{ij} \qquad H = \sum_{ij} J_{ij}^\top \Sigma_{ij}^{-1} J_{ij}$$
2. Solve the linear system to get new increment
$$H\Delta\mathbf{x} = -\mathbf{b}$$
3. Update previous estimate
$$\mathbf{x} \leftarrow \mathbf{x} + \Delta\mathbf{x}$$

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Sparsity of the Hessian

- The Hessian is
  - positive semi-definit
  - symmetric
  - sparse
- This allows the use of efficient solvers
  - Sparse Cholesky decomposition (~100M matrix elements)
  - Preconditioned conjugate gradients (~1.000 matrix elements)
  - ... many others

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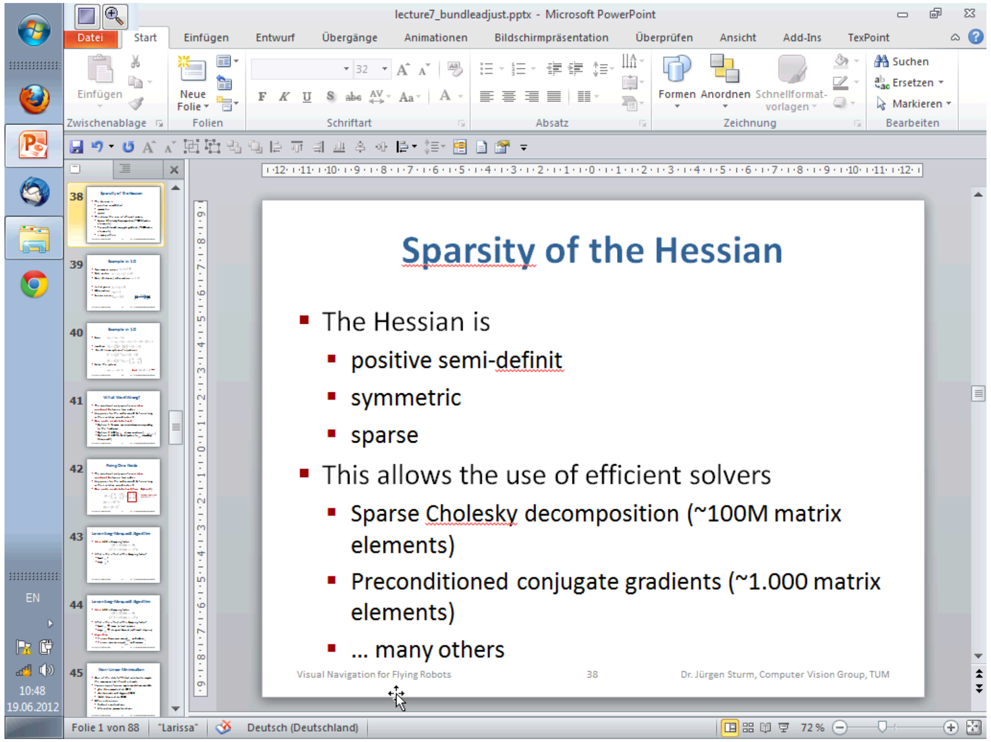


Example in 1D

- Error $e_{12} = z_{12} - \bar{z}_{12}$

$$= z_{12} - (c_2 - c_1) = 1 - (0 - 0) = 1$$

- Jacobian $J_{12} = \begin{pmatrix} \frac{\partial e_{12}}{\partial c_1} & \frac{\partial e_{12}}{\partial c_2} \end{pmatrix} = \begin{pmatrix} 1 & -1 \end{pmatrix}$
- Build linear system of equations

$$b^\top = e_{12}^\top \Sigma^{-1} e_{12} = \begin{pmatrix} 2 & -2 \end{pmatrix}$$

$$H = J_{12}^\top \Sigma^{-1} J_{12} = \begin{pmatrix} 2 & -2 \\ -2 & 2 \end{pmatrix}$$

- Solve the system

$$\Delta x = -H^{-1} b$$

but $\det H = 0$ **???**

What Went Wrong?

- The constraint only specifies a **relative constraint** between two nodes
- Any poses for the nodes would be fine as long as their relative coordinates fit
- **One node needs to be fixed**
  - Option 1: Remove one row/column corresponding to the fixed pose
  - Option 2: Add to $H, \mathbf{b}$ a linear constraint $1 \cdot \Delta c_1 = 0$
  - Option 3: Add the identity matrix to H (Levenberg-Marquardt)

Fixing One Node

- The constraint only specifies a **relative constraint** between two nodes
- Any poses for the nodes would be fine as long as their relative coordinates fit
- **One node needs to be fixed (here: Option 2)**

$$H = \begin{pmatrix} 2 & -2 \\ -2 & 2 \end{pmatrix} + \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix}$$

additional constraint that sets $\Delta c_1 = 0$

$$\Delta x = -H^{-1} b$$

$$\Delta x = \begin{pmatrix} 0 & 1 \end{pmatrix}^\top$$

Levenberg-Marquardt Algorithm

- **Idea:** Add a damping factor

$$(H + \lambda I)\Delta \mathbf{x} = -\mathbf{b}$$

$$(J^\top J + \lambda I)\Delta \mathbf{x} = -J^\top \mathbf{e}$$

- What is the effect of this damping factor?
  - Small λ?
  - Large λ?

Non-Linear Minimization

- One of the state-of-the-art solution to compute the maximum likelihood estimate
- Various open-source implementations available
  - g2o [Kuemmerle et al., 2011]
  - sba [Lourakis and Argyros, 2009]
  - iSAM [Kaess et al., 2008]
- Other extensions:
  - Robust error functions
  - Alternative parameterizations

Bundle Adjustment

- **Graph SLAM:** Optimize (only) the camera poses

$$\mathbf{x} = (\mathbf{c}_1^\top, \ldots, \mathbf{c}_n^\top)^\top \in \mathbb{R}^{6n}$$

- **Bundle Adjustment:** Optimize both 6DOF camera poses and 3D (feature) points

$$\mathbf{x} = (\underbrace{\mathbf{c}_1^\top, \ldots, \mathbf{c}_n^\top}_{\mathbf{c} \in \mathbb{R}^{6n}}, \underbrace{\mathbf{p}_1^\top, \ldots, \mathbf{p}_m^\top}_{\mathbf{p} \in \mathbb{R}^{3m}})^\top \in \mathbb{R}^{6n+3m}$$

- Typically $m \gg n$ (why?)

Error Function

- Camera pose $\mathbf{c}_i \in \mathbb{R}^6$
- Feature point $\mathbf{p}_j \in \mathbb{R}^3$
- Observed feature location $\mathbf{z}_{ij} \in \mathbb{R}^2$
- Expected feature location

$$g(\mathbf{c}_i, \mathbf{p}_j) = R_i^\top (\mathbf{t}_i - \mathbf{p}_j)$$

$$h(\mathbf{c}_i, \mathbf{p}_j) = g_{x,y}(\mathbf{c}_i, \mathbf{p}_j) / g_z(\mathbf{c}_i, \mathbf{p}_j)$$

Error Function

- Difference between observation and expectation

$$\mathbf{e}_{ij} = \mathbf{z}_{ij} - h(\mathbf{c}_i, \mathbf{p}_j)$$

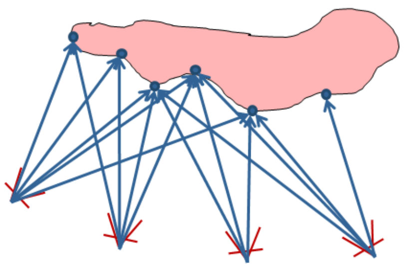
- Error function

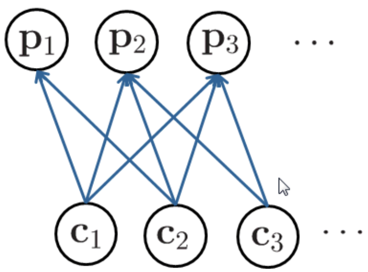
$$f(\mathbf{c}, \mathbf{p}) = \sum_{ij} \mathbf{e}_{ij}^\top \Sigma^{-1} \mathbf{e}_{ij}$$

- Covariance Σ is often chosen isotropic and on the order of one pixel

Illustration of the Structure

- Each camera sees several points
- Each point is seen by several cameras
- Cameras are independent of each other (given the points), same for the points





Primary Structure

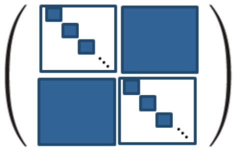
- Characteristic structure

$$\begin{pmatrix} J_\mathbf{c}^\top J_\mathbf{c} & J_\mathbf{c}^\top J_\mathbf{p} \\ J_\mathbf{p}^\top J_\mathbf{c} & J_\mathbf{p}^\top J_\mathbf{p} \end{pmatrix} \begin{pmatrix} \Delta\mathbf{c} \\ \Delta\mathbf{p} \end{pmatrix} = \begin{pmatrix} -J_\mathbf{c}^\top \mathbf{e}_\mathbf{c} \\ -J_\mathbf{p}^\top \mathbf{e}_\mathbf{p} \end{pmatrix}$$

$$\begin{pmatrix} H_\mathbf{cc} & H_\mathbf{cp} \\ H_\mathbf{pc} & H_\mathbf{pp} \end{pmatrix} \begin{pmatrix} \Delta\mathbf{c} \\ \Delta\mathbf{p} \end{pmatrix} = \begin{pmatrix} -J_\mathbf{c}^\top \mathbf{e}_\mathbf{c} \\ -J_\mathbf{p}^\top \mathbf{e}_\mathbf{p} \end{pmatrix}$$

Primary Structure

- **Insight:** $H_{\mathbf{cc}}$ and $H_{\mathbf{pp}}$ are block-diagonal (because each constraint depends only on one camera and one point)



$$\begin{pmatrix}\Delta\mathbf{c}\\ \Delta\mathbf{p}\end{pmatrix} = \begin{pmatrix}-J_{\mathbf{c}}^{\top}\mathbf{e}_{\mathbf{c}}\\ -J_{\mathbf{p}}^{\top}\mathbf{e}_{\mathbf{p}}\end{pmatrix}$$

- This can be efficiently solved using the Schur Complement

Schur Complement

- Given: Linear system

$$\begin{pmatrix}A & B\\ C & D\end{pmatrix}\begin{pmatrix}\mathbf{x}\\ \mathbf{y}\end{pmatrix} = \begin{pmatrix}\mathbf{a}\\ \mathbf{b}\end{pmatrix}$$

- If D is invertible, then (using Gauss elimination)

$$(A - BD^{-1}C)\mathbf{x} = \mathbf{a} - BD^{-1}\mathbf{b}$$
$$\mathbf{y} = D^{-1}(\mathbf{b} - C\mathbf{x})$$

- **Reduced complexity**, i.e., invert one $p \times p$ and $p \times p$ matrix instead of one $(p+q) \times (p+q)$ matrix

Schur Complement

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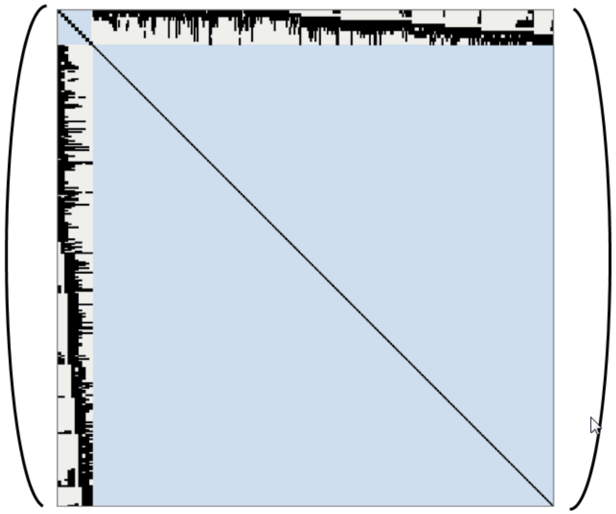
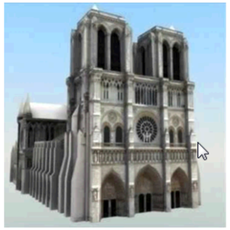
Example Hessian (Lourakis and Argyros, 2009)

$H =$



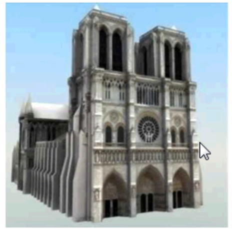
From Sparse Maps to Dense Maps

- So far, we only looked at sparse 3D maps
  - We know where the (sparse) cameras are
  - We know where the (sparse) 3D feature points are
- How can we turn these models into volumetric 3D models?

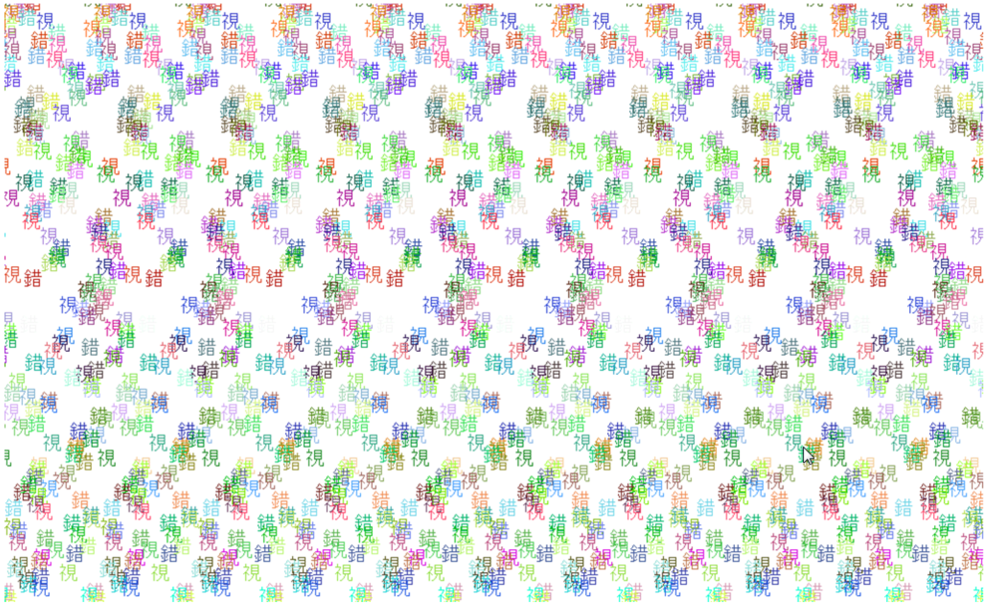


From Sparse Maps to Dense Maps

- **Today:** Estimation of depth dense images (stereo cameras, laser triangulation, structured light/Kinect)
- **Next week:** Dense map representations and data fusion

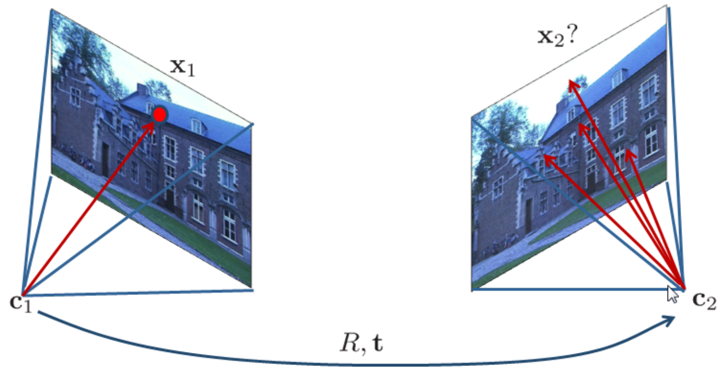


Human Stereo Vision



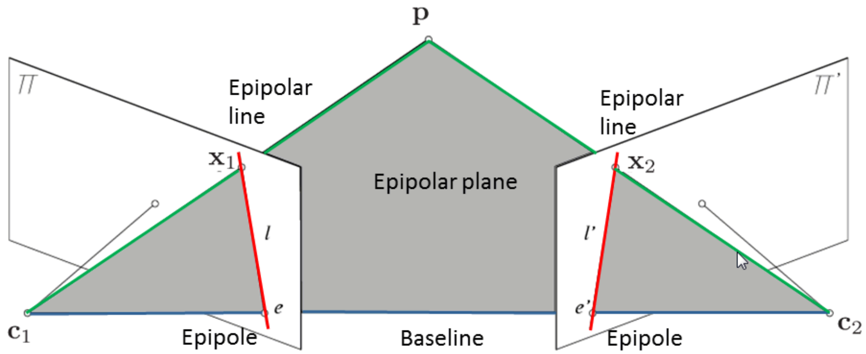
Stereo Correspondence Constraints

- Given a point in the left image, where can the corresponding point be in the right image?



Reminder: Epipolar Geometry

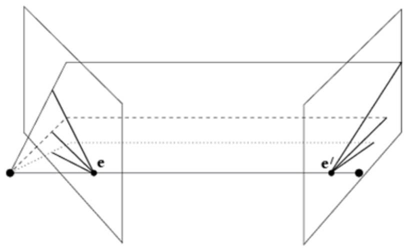
- A point in one image "generates" a line in another image (called the **epipolar line**)
- Epipolar constraint $\hat{\mathbf{x}}_2^\top E \hat{\mathbf{x}}_1 = 0$

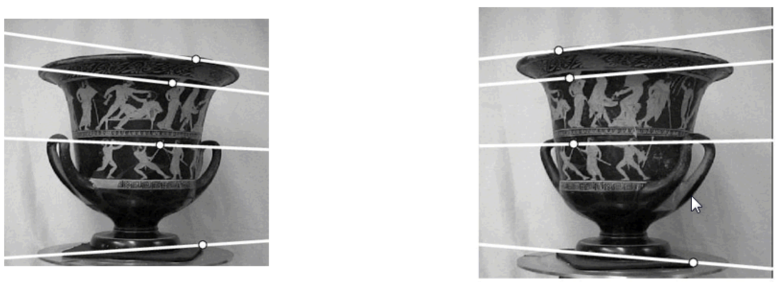


Epipolar Constraint

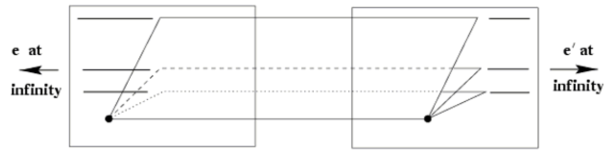
- This is useful because it reduces the correspondence problem to a 1D search along an epipolar line

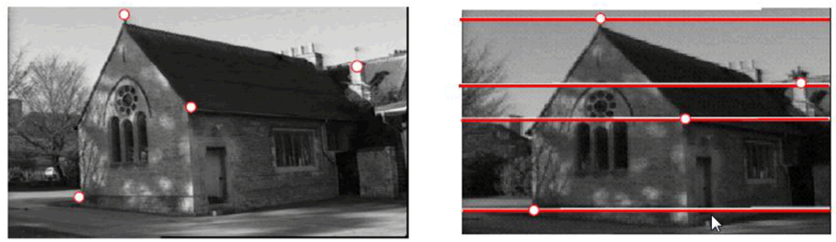
Example: Converging Cameras





Example: Parallel Cameras



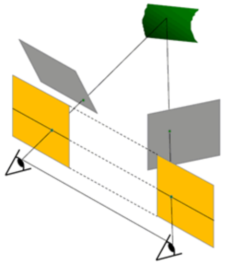


Rectification

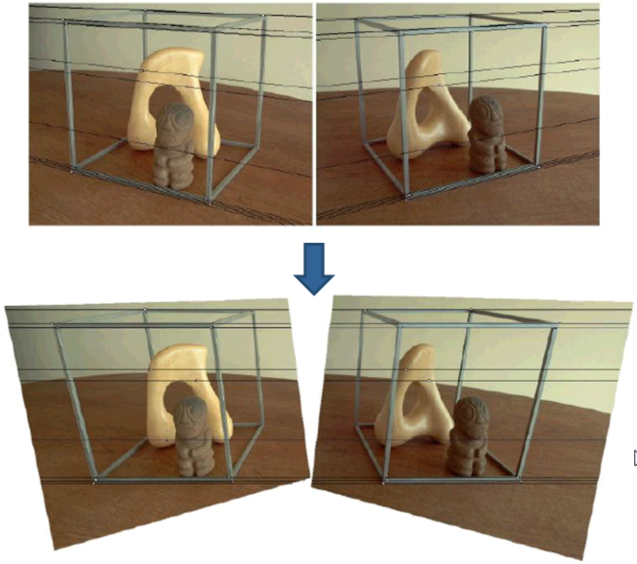
- In practice, it is convenient if the image scanlines (rows) are the epipolar lines

→ Reproject image planes onto a common plane parallel to the baseline (two 3x3 homographies)

- Afterwards pixel motion is horizontal

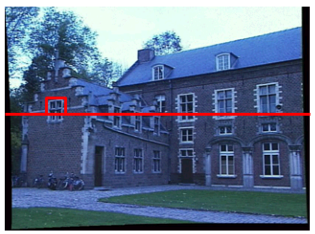


Example: Rectification



Basic Stereo Algorithm

- For each pixel in the left image
  - Compare with every pixel on the same epipolar line in the right image
  - Pick pixel with minimum matching cost (noisy)
  - Better: match small blocks/patches (SSD, SAD, NCC)



left image

right image

Block Matching Algorithm

Input: Two images and camera calibrations

Output: Disparity (or depth) image

Algorithm:

1. Geometry correction (undistortion and rectification)
2. Matching cost computation along search window
3. Extrema extraction (at sub-pixel accuracy)
4. Post-filtering (clean up noise)

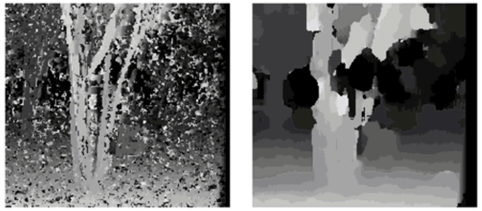
Example

- Input

- Output

What is the Influence of the Block Size?

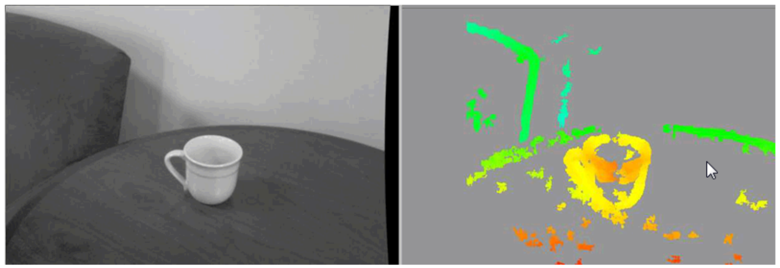
- Common choices are 5x5 .. 11x11
- Smaller neighborhood: more details
- Larger neighborhood: less noise
- Suppress pixels with low confidence (e.g., check ratio best match vs. 2nd best match)



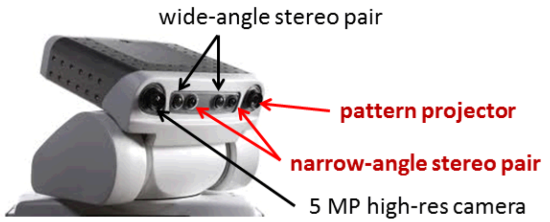
3x3 20x20

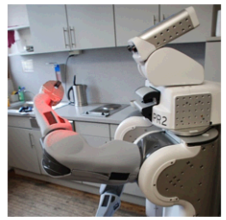
Problems with Stereo

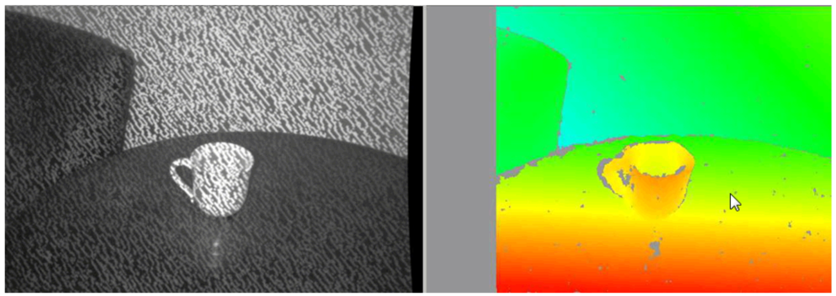
- Block matching typically fails in regions with low texture
  - Global optimization/regularization (speciality of our research group)
  - Additional texture projection



Example: PR2 Robot with Projected Texture Stereo







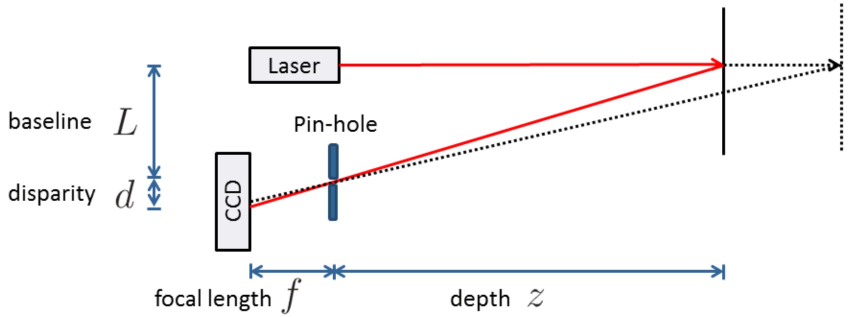
Laser Triangulation

Idea:

- Well-defined light pattern (e.g., point or line) projected on scene
- Observed by a line/matrix camera or a position-sensitive device (PSD)
- Simple triangulation to compute distance

Laser Triangulation

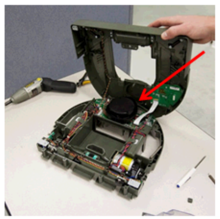
- Function principle

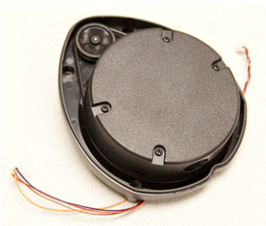


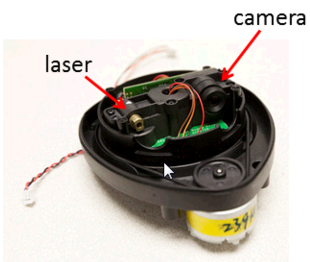
- Depth triangulation $z = f\frac{L}{d}$
  (note: same for stereo disparities)

Example: Neato XV-11

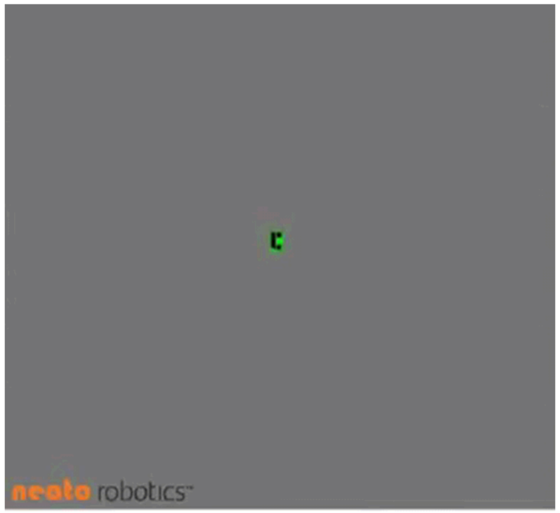
- K. Konolige, "A low-cost laser distance sensor", ICRA 2008
- Specs: 360deg, 10Hz, 30 USD





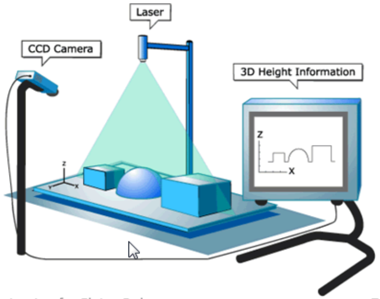


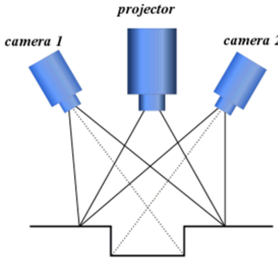
How Does the Data Look Like?



Laser Triangulation

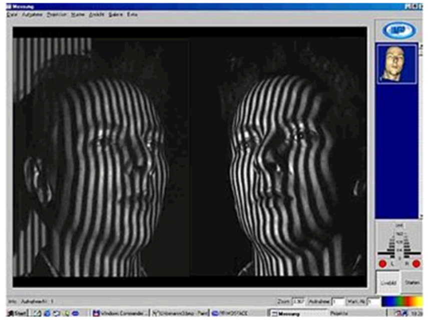
- Stripe laser + 2D camera
- Often used on conveyer belts (volume sensing)
- Large baseline gives better depth resolution but more occlusions → use two cameras





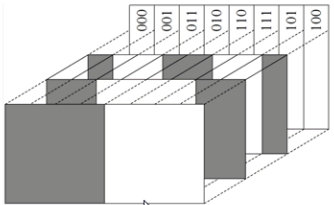
Structured Light

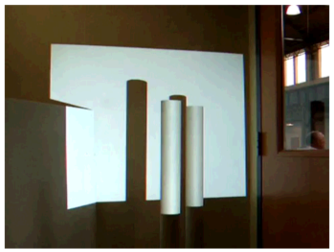
- Multiple stripes / 2D pattern
- Data association more difficult



Structured Light

- Multiple stripes / 2D pattern
- Data association more difficult
- Coding schemes
  - Temporal: Coded light





Structured Light

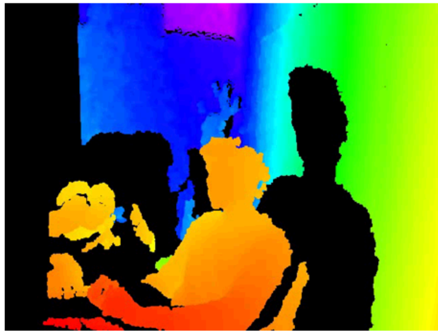
- Multiple stripes / 2D pattern
- Data association more difficult
- Coding schemes
  - Temporal: Coded light
  - Wavelength: Color
  - Spatial: Pattern (e.g., diffraction patterns)

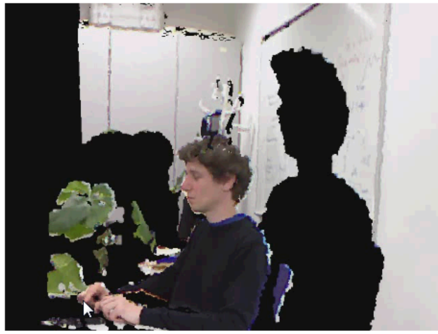
Sensor Principle of Kinect

- Kinect projects a diffraction pattern (speckles) in near-infrared light
- CMOS IR camera observes the scene

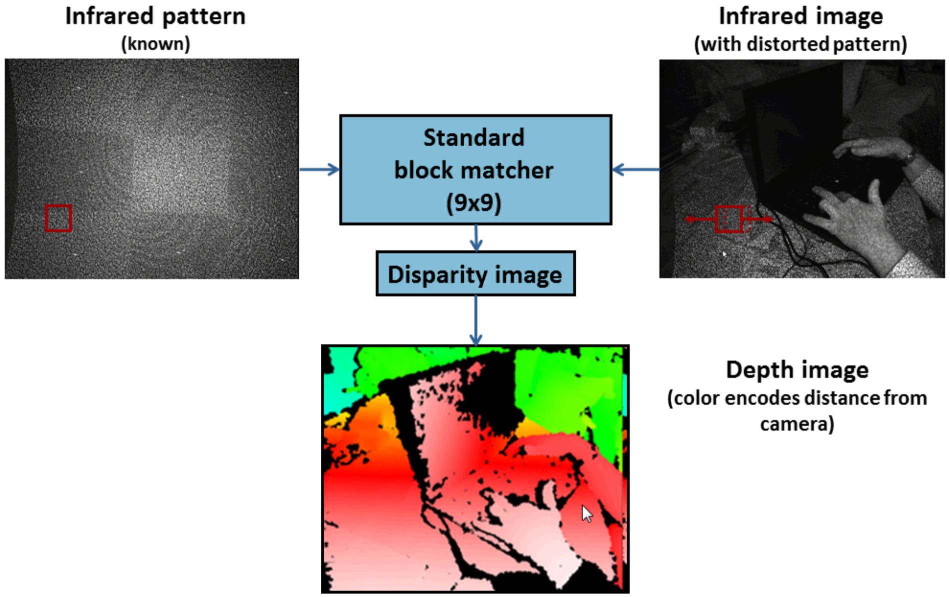
Example Data

- Kinect provides color (RGB) and depth (D) video
- This allows for novel approaches for (robot) perception





Sensor Principle of Kinect



Sensor Principle of Kinect

- Pattern is memorized at a known depth
- For each pixel in the IR image
  - Extract 9x9 template from memorized pattern
  - Correlate with current IR image over 64 pixels and search for the maximum
  - Interpolate maximum to obtain sub-pixel accuracy (1/8 pixel)
  - Calculate depth by triangulation

Technical Specs

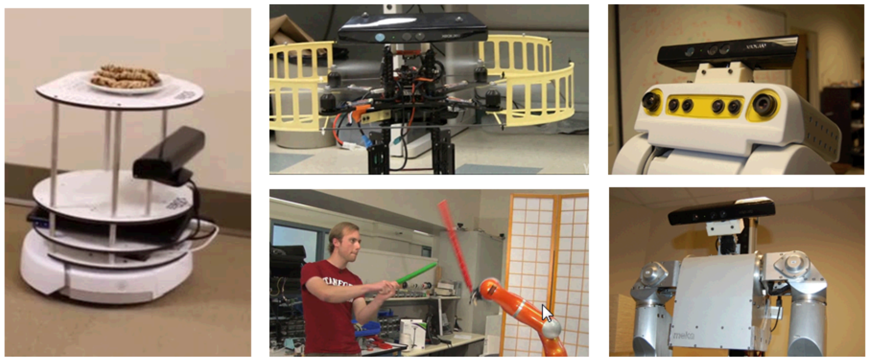
- Infrared camera has 640x480 @ 30 Hz
  - Depth correlation runs on FPGA
  - 11-bit depth image
  - 0.8m – 5m range
  - Depth sensing does not work in direct sunlight (why?)
- RGB camera has 640x480 @ 30 Hz
  - Bayer color filter
- Four 16-bit microphones with DSP for beam forming @ 16kHz
- Requires 12V (for motor), weighs 500 grams
- Human pose recognition runs on Xbox CPU and uses only 10-15% processing power @30 Hz
(Paper: http://research.microsoft.com/apps/pubs/default.aspx?id=145347)

History

- 2005: Developed by PrimeSense (Israel)
- 2006: Offer to Nintendo and Microsoft, both companies declined
- 2007: Alex Kidman becomes new incubation director at Microsoft, decides to explore PrimeSense device. Johnny Lee assembles a team to investigate technology and develop game concepts
- 2008: The group around Prof. Andrew Blake and Jamie Shotton (Microsoft Research) develops pose recognition
- 2009: The group around Prof. Dieter Fox (Intel Labs / Univ. of Washington) works on RGB-D mapping and RGB-D object recognition
- Nov 4, 2010: Official market launch
- Nov 10, 2010: First open-source driver available
- 2011: First programming competitions (ROS 3D, PrimeSense), First workshops (RSS, Euron)
- 2012: First special Issues (JVCI, T-SMC)

Impact of the Kinect Sensor

- Sold >18M units, >8M in first 60 days (Guiness: "fastest selling consumer electronics device)
- Has become a "standard" sensor in robotics



Kinect: Applications

Open Research Questions

- How can RGB-D sensing facilitate in solving hard perception problems in robotics?
  - Interest points and feature descriptors?
  - Simultaneous localization and mapping?
  - Collision avoidance and visual navigation?
  - Object recognition and localization?
  - Human-robot interaction?
  - Semantic scene interpretation?

Ende der Bildschirmpräsentation. Zum Beenden klicken.