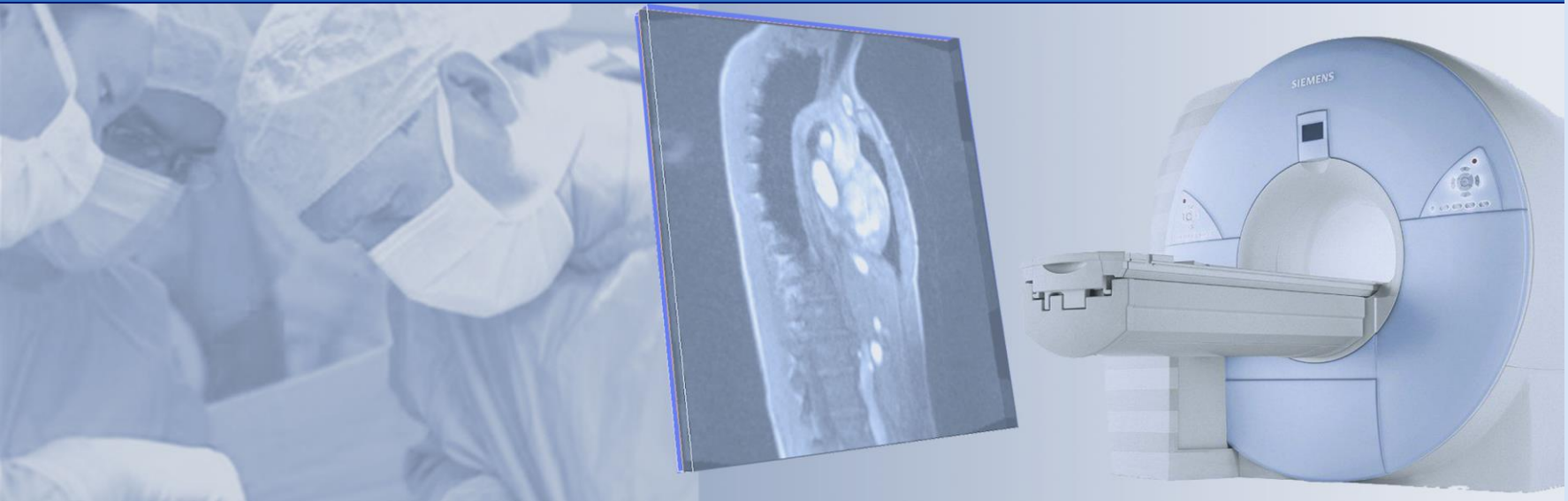


Computer- and robot-assisted Surgery



NATIONALES CENTRUM
FÜR TUMORERKRANKUNGEN
PARTNERSTANDORT DRESDEN
UNIVERSITÄTS KREBSCENTRUM UCC

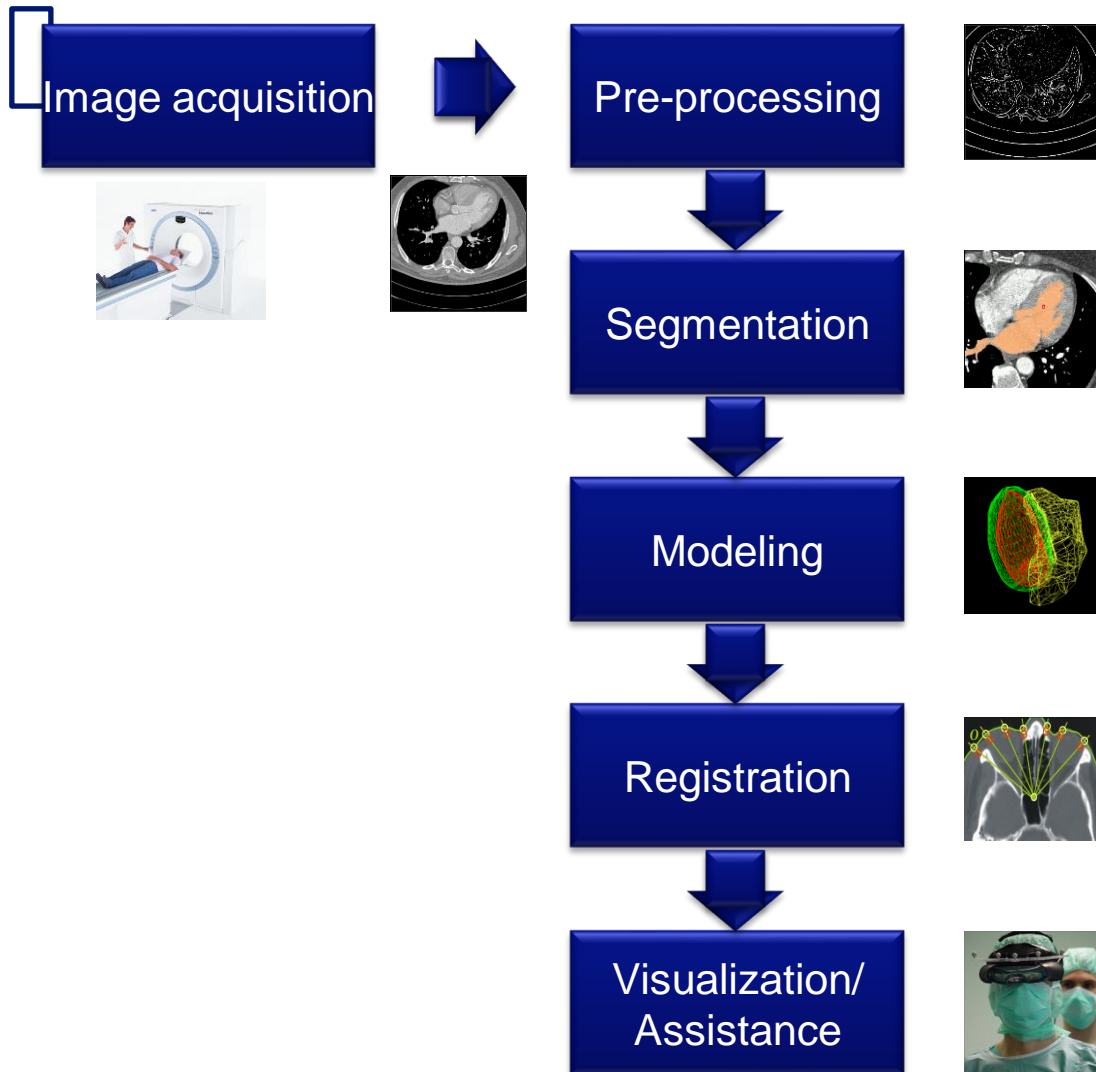
getragen von:

Deutsches Krebsforschungszentrum
Universitätsklinikum Carl Gustav Carus Dresden
Medizinische Fakultät Carl Gustav Carus, TU Dresden
Helmholtz-Zentrum Dresden-Rossendorf

Lecture 7

Basics of Computer Vision – Part 2

Process chain computer-assisted surgery



Interaction and Feedback

- <https://pingo.coactum.de> -> 392473



Image representation

- Context:



- Digitalization: Discretization + Quantization

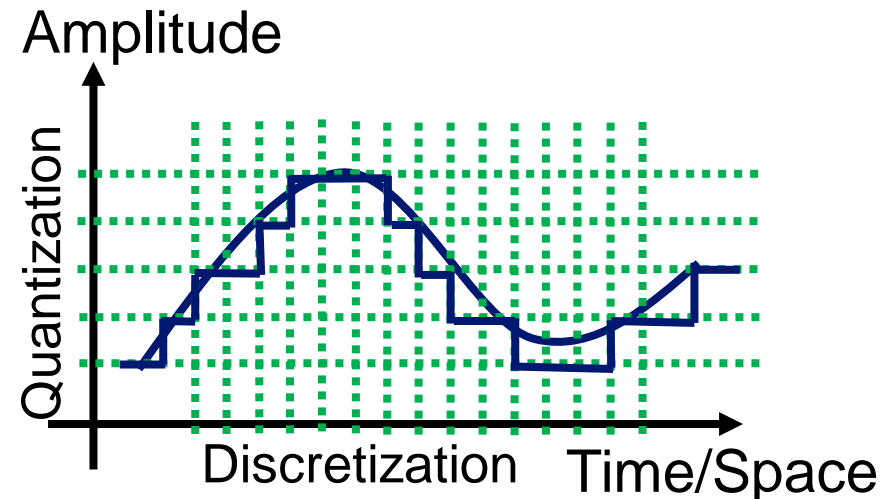
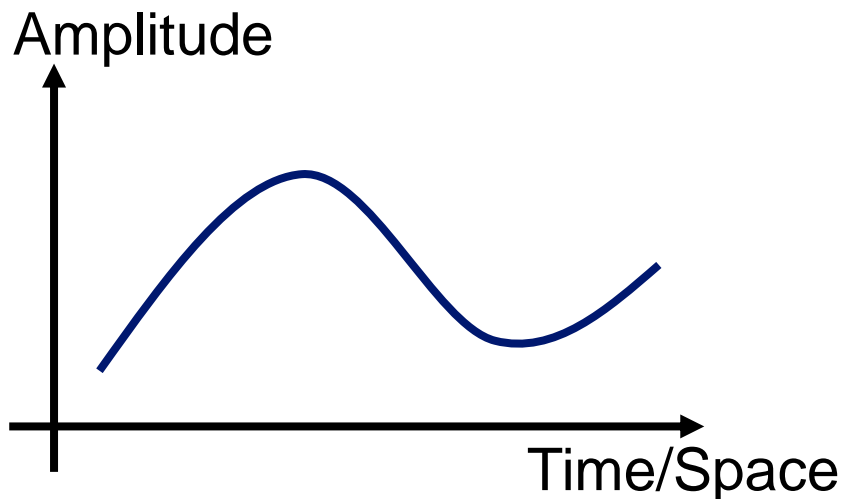


Image representation

2D grayscale image: Discrete function

$$\text{Img} : [0..n] \times [0..m] \rightarrow [0..q]$$
$$(x, y) \mapsto G(x, y) = g$$

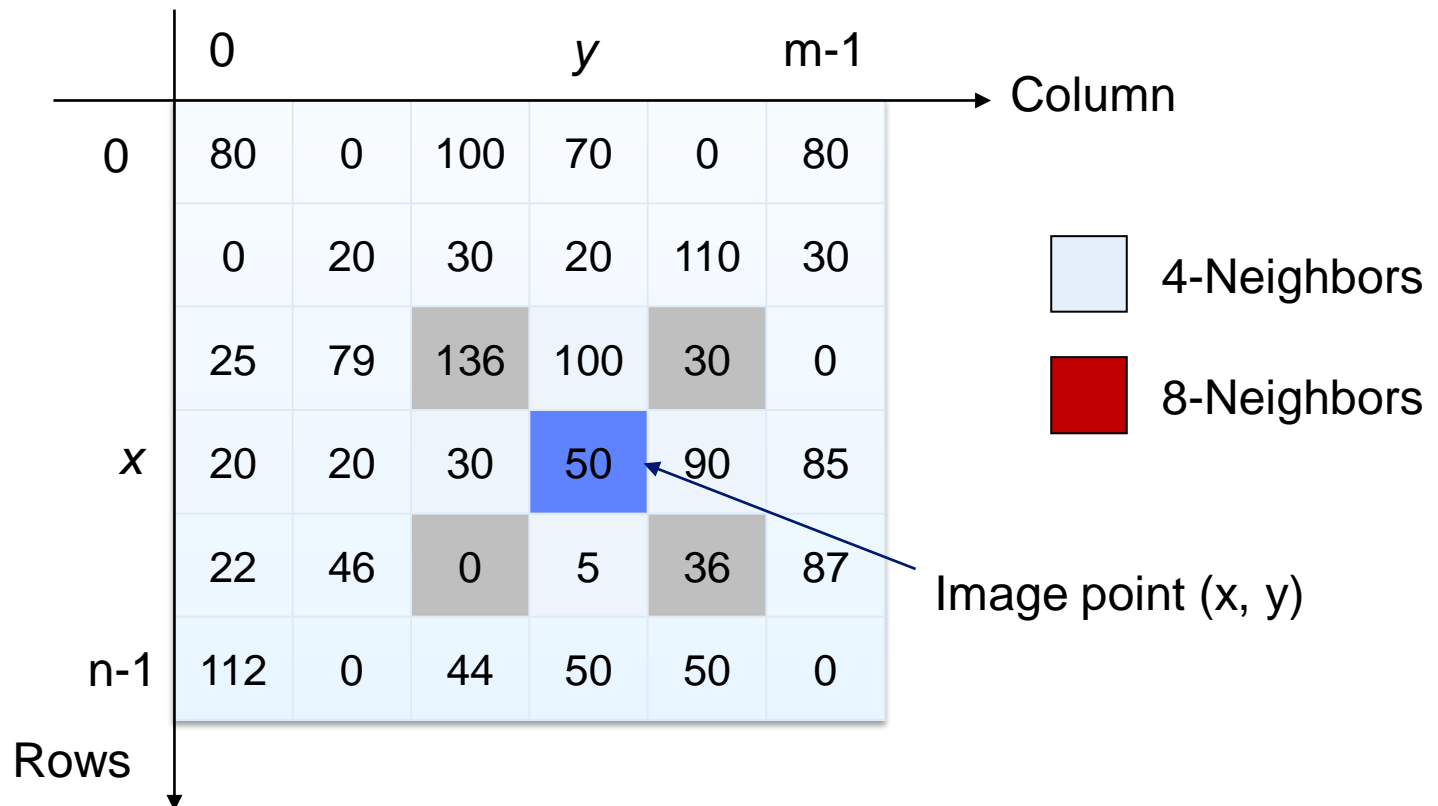
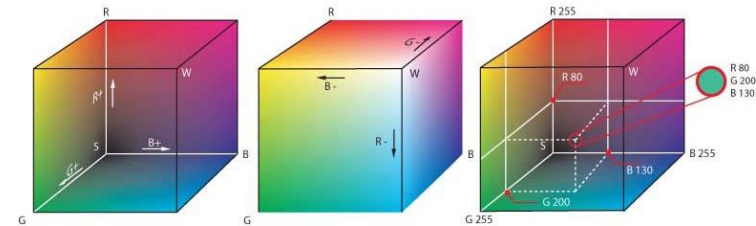
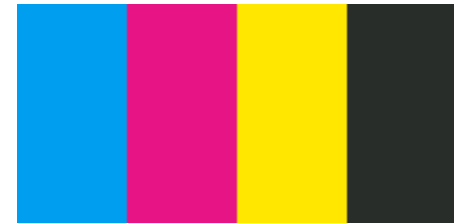


Image representation

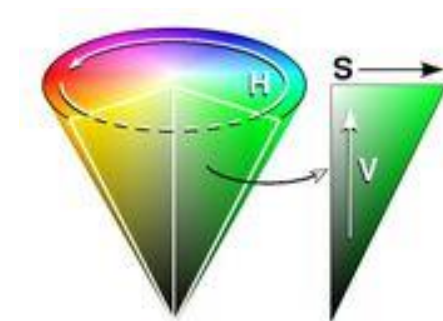
- Color image: different models for different applications
 - B/W: Grayscale
 - RGB-model: specific for screens (Phosphor-crystals), very common
 - CMYK-model: Color printer (subtractive color mix)
 - YCbCr: Breakdown into luminescence Y und two color components Cb, Cr
 - HSV (Hue, Saturation, Value): specific for color segmentation



RGB



CMYK



HSV

Quelle: Wikipedia

Image representation

- RGB-model:

$$\begin{aligned} \text{Img} : [0..n] \times [0..m] &\rightarrow [0..R] \times [0..G] \times [0..B] \\ (x, y) &\mapsto G(x, y) = (r, g, b) \end{aligned}$$

3 components: red, green and blue

usually $256 \times 256 \times 256$ nuances = 16,8 Mio. colors

Image representation

Conversion between different models

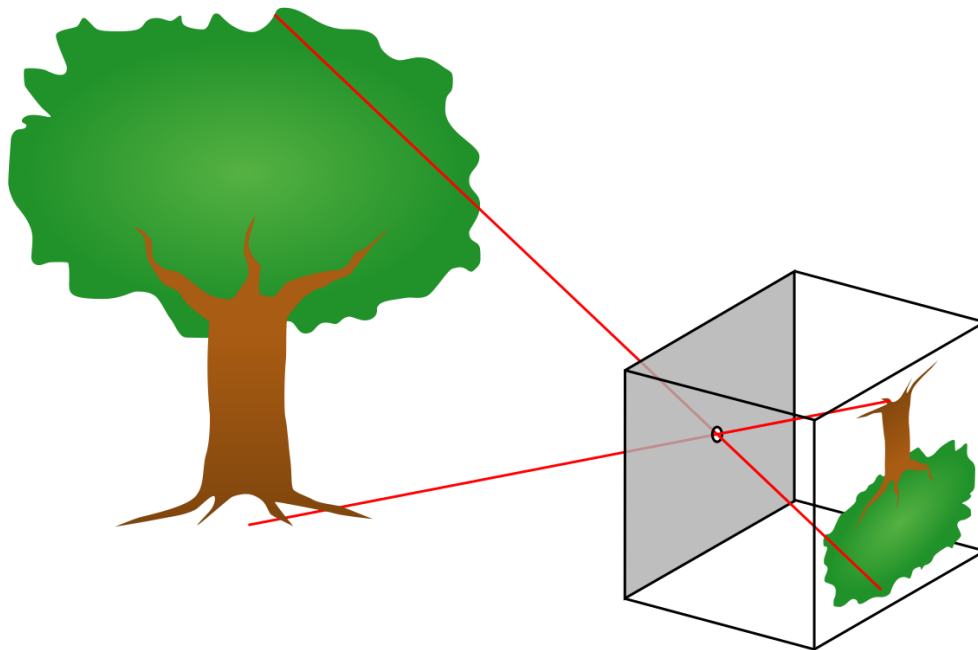
- RGB to B/W: $I = \frac{R+G+B}{3}$
- RGB to HSV: $V = \text{MAX}(R, G, B)$ or $V = \frac{R+G+B}{3}$

$$S = 1 - \frac{\text{MIN}(R, G, B)}{V} \text{ or } S = \begin{cases} \frac{3}{2}(R - V), & B + R \geq 2G \\ \frac{3}{2}(V - B), & B + R < 2G \end{cases}$$

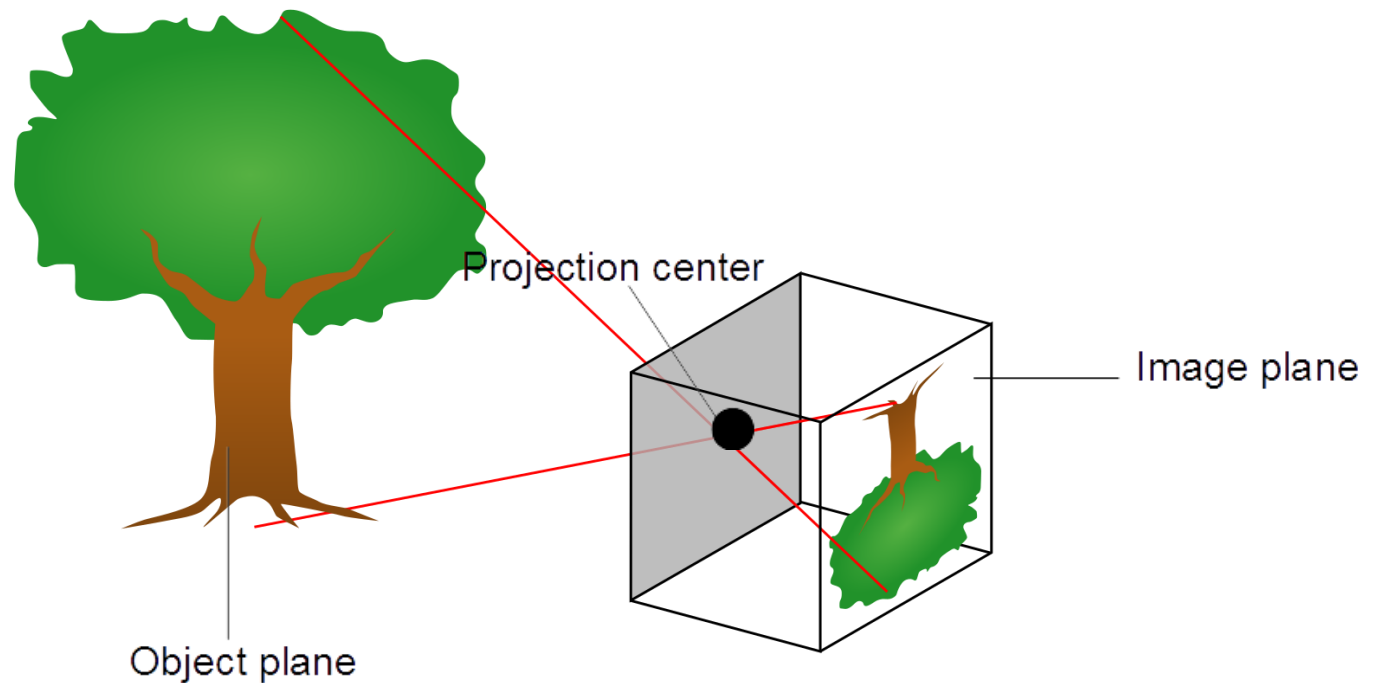
$$H = \begin{cases} 60^\circ \left(0 + \frac{G - B}{\text{MAX}(R, G, B) - \text{MIN}(R, G, B)}\right), & R = \text{MAX}(R, G, B) \\ 60^\circ \left(2 + \frac{B - R}{\text{MAX}(R, G, B) - \text{MIN}(R, G, B)}\right), & G = \text{MAX}(R, G, B) \\ 60^\circ \left(4 + \frac{R - G}{\text{MAX}(R, G, B) - \text{MIN}(R, G, B)}\right), & B = \text{MAX}(R, G, B) \end{cases}$$
$$H < 0^\circ \Rightarrow H = H + 360^\circ$$

Pinhole camera model

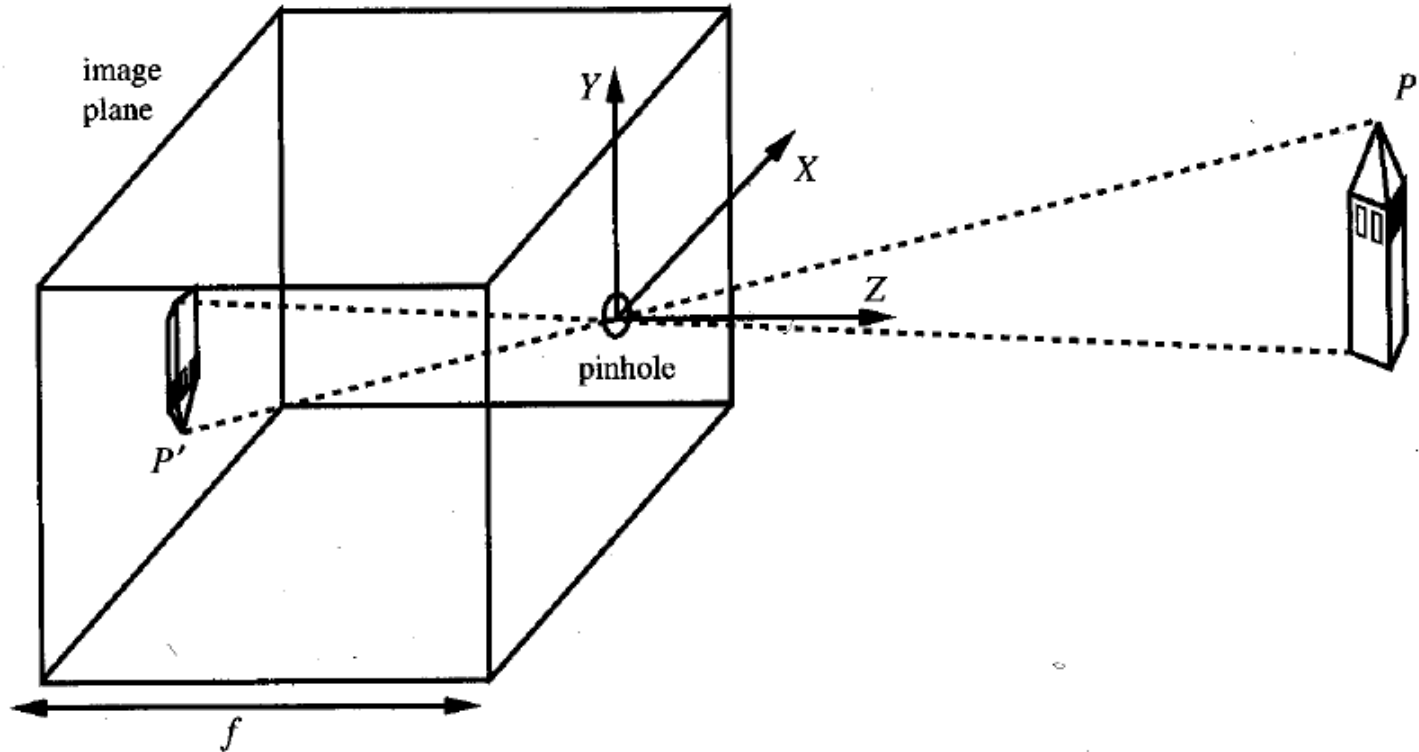
- Describes mathematical relationship between coordinates in 3D and their projection on a 2D plane
 - Simple model
 - No modeling of lens
 - No world coordinate system



Pinhole camera model



Pinhole camera model



Projection of 3D point $P = (x, y, z)$ onto an image point $p = (u, v, w)$ with focal length f :

$$-\frac{u}{f} = \frac{x}{z} \quad -\frac{v}{f} = \frac{y}{z} \quad w = -f$$

$$x = -\frac{uz}{f} \quad y = -\frac{vz}{f}$$

$$p = \begin{pmatrix} u \\ v \\ w \end{pmatrix} = \begin{pmatrix} u \\ v \\ -f \end{pmatrix} = -\frac{f}{z} \begin{pmatrix} x \\ y \\ z \end{pmatrix} = -\frac{f}{z} P$$

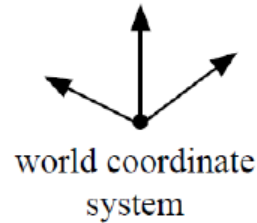
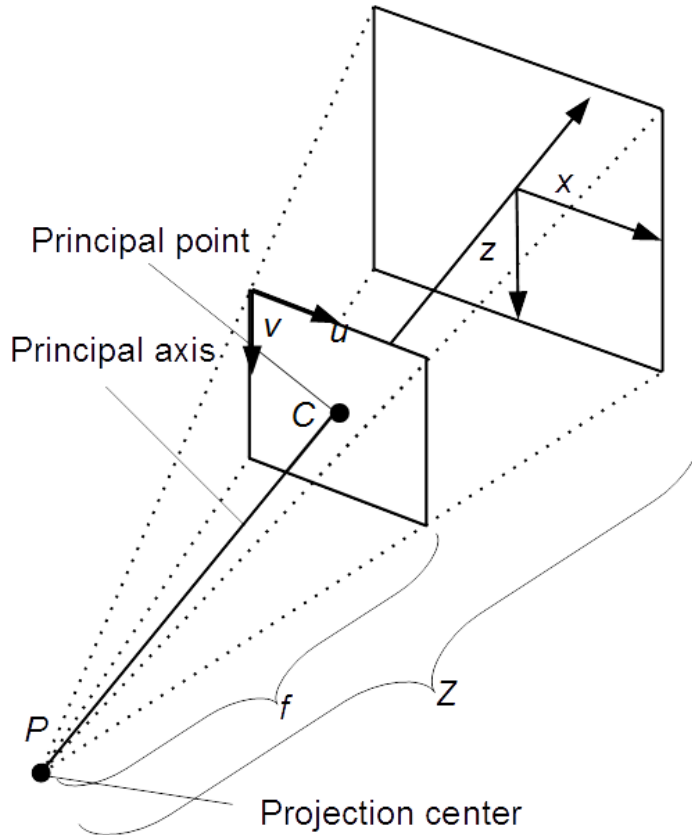
Back projection

Extended camera model

- Pinhole camera model strongly simplifies reality
 - Image origin identical with principle point
 - Pixels are square
 - No lens distortion
 - No world coordinate system
- Therefore in practice, extensions are used
- A few definitions:
 - Principal axis: Line through the projection center, orthogonal to image plane
 - Principal point C : Point of intersection of principal axis and image plane
 - Image coordinate system: 2D, unit [pixels]. Origin in the upper left corner u-axis to the right, v-axis to the bottom
 - Camera coordinate system: 3D, unit [mm]. Origin in the projection center, axis parallel to those of the image coordinate system (x to u, y to v and z away from the projection center)
 - World coordinate system: 3D, unit [mm]. Origin arbitrary, anywhere in space possible

Extended camera model

- Common variant: Pinhole camera model in positive position



$$\begin{pmatrix} u \\ v \\ w \end{pmatrix} = -\frac{f}{z} \begin{pmatrix} x \\ y \\ z \end{pmatrix} \Rightarrow \begin{pmatrix} u \\ v \\ w \end{pmatrix} = \frac{f}{z} \begin{pmatrix} x \\ y \\ z \end{pmatrix}$$

- Projection center behind image plane
- No mirroring (negative signs are omitted)

Extended camera model

- Intrinsic parameters
 - Focal length f
 - In practice, the conversion from [mm] to [pixel] is incorporated into the focal length
 - As we assume non-quadratic but rectangular pixels, there is a parameter for each direction: f_x, f_y
 - Since product of actual focal length [mm] and conversion factor [pixel/mm] they have the unit [pixel]
 - Principal point $c(c_x, c_y)$
 - Point of intersection of principle axis and image plane
 - Has to be taken into consideration when moving origin of image plane

$$\begin{pmatrix} u \\ v \\ w \end{pmatrix} = \frac{f}{z} \begin{pmatrix} x \\ y \\ z \end{pmatrix} \quad \Rightarrow \quad \begin{pmatrix} u \\ v \end{pmatrix} = \frac{1}{z} \begin{pmatrix} f_x \cdot x \\ f_y \cdot y \end{pmatrix} + \begin{pmatrix} c_x \\ c_y \end{pmatrix}$$

Which of the following coordinate systems is NOT in 3D?

- A: Image coordinate system
- B: Camera coordinate system
- C: World coordinate system
- D: None of the above

Homogenous coordinates

$$\begin{pmatrix} u \\ v \end{pmatrix} = \frac{1}{z} \begin{pmatrix} f_x \cdot x \\ f_y \cdot y \end{pmatrix} + \begin{pmatrix} c_x \\ c_y \end{pmatrix} \text{ can be expressed better}$$

- Homogenous coordinates
 - Add a new dimension with value of 1 to vector, e.g.: $\begin{pmatrix} x \\ y \\ z \end{pmatrix} \rightarrow \begin{pmatrix} x \\ y \\ z \\ 1 \end{pmatrix}$ $\begin{pmatrix} u \\ v \end{pmatrix} \rightarrow \begin{pmatrix} u \\ v \\ 1 \end{pmatrix}$
- Allows expression of certain operations with matrix multiplication

$$\begin{pmatrix} u \\ v \end{pmatrix} = \frac{1}{z} \begin{pmatrix} f_x \cdot x \\ f_y \cdot y \end{pmatrix} + \begin{pmatrix} c_x \\ c_y \end{pmatrix} \rightarrow \begin{pmatrix} u \cdot w \\ v \cdot w \\ w \end{pmatrix} = \begin{pmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{pmatrix} \cdot \begin{pmatrix} x \\ y \\ z \end{pmatrix}$$

- Afterwards, normalize so the “additional” dimension becomes 1:

$$\frac{1}{w} \cdot \begin{pmatrix} u \cdot w \\ v \cdot w \\ w \end{pmatrix} = \begin{pmatrix} u \\ v \\ 1 \end{pmatrix} \rightarrow \begin{pmatrix} u \\ v \end{pmatrix}$$

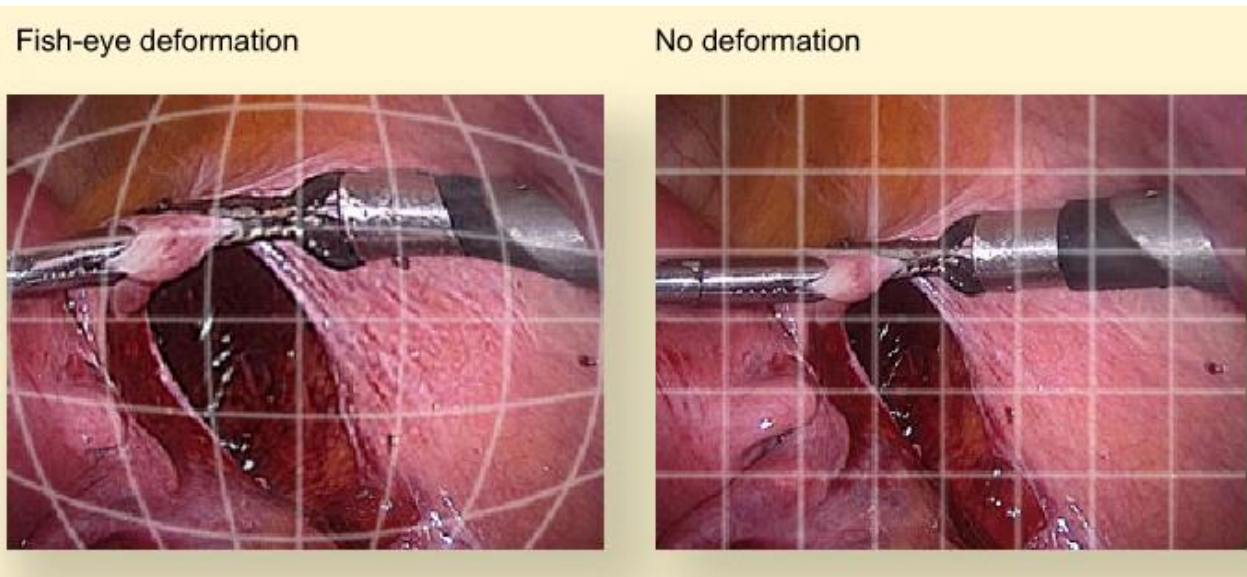
Extended camera model

- Intrinsic parameters
 - Focal length f
 - In practice, the conversion from [mm] to [pixel] is incorporated into the focal length
 - As we assume non-quadratic but rectangular pixels, there is a parameter for each direction: f_x, f_y
 - Since product of actual focal length [mm] and conversion factor [pixel/mm] they have the unit [pixel]
 - Principal point $\mathbf{c}(c_x, c_y)$
 - Point of intersection of principal axis and image plane
 - Has to be taken into consideration when moving origin of image plane
 - Contained in the camera matrix K

$$K = \begin{pmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{pmatrix}$$

Lens distortion

- Wide angle lenses (often encountered in endoscope) can significantly distort the image
 - Radial distortion
 - Symmetric from principle point
 - Other types of distortion are possible



Extended camera model

- Intrinsic parameters

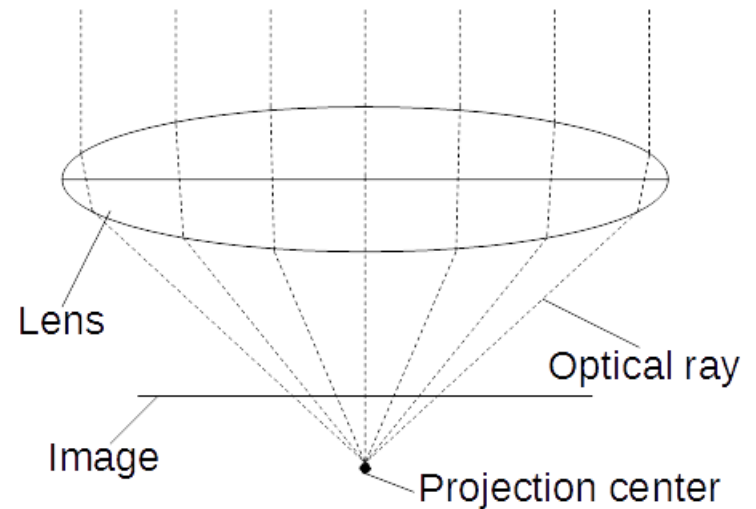
- Radial lens distortion
 - Project points “back onto lens”:

$$\begin{pmatrix} x_n \\ y_n \end{pmatrix} := \begin{pmatrix} \frac{u - c_x}{f_x} \\ \frac{v - c_y}{f_y} \end{pmatrix}$$

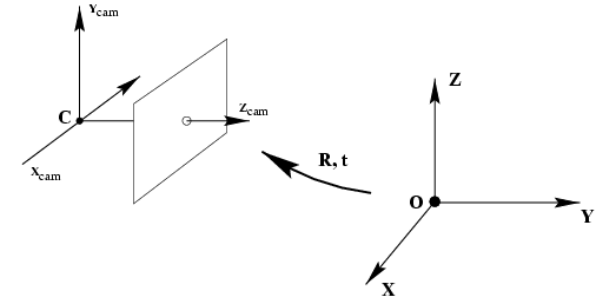
- Distortion is proportional to distance from principle point $r := \sqrt{x_n^2 + y_n^2}$
- The distorted coordinate can then be computed from a distortion model
- Often approximated using first two or three terms of a Taylor polynomial

$$\begin{pmatrix} x_d \\ y_d \end{pmatrix} = (1 + \mathbf{d}_1 r^2 + \mathbf{d}_2 r^4 + \dots) \begin{pmatrix} x_n \\ y_n \end{pmatrix}$$

- Images can be “undistorted” by using a lookup table and interpolation



Extended camera model



- Extrinsic parameters

- Offset camera to world coordinate, e.g. when using multiple cameras or a robot
- Transformation from world to camera coordinate system
- Defined through a coordinate transform consisting of
 - Rotation matrix R

$$R = R_z(\gamma)R_y(\beta)R_x(\alpha)$$

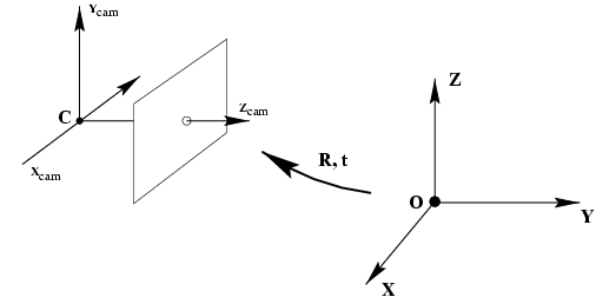
$$R_x(\alpha) = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos(\alpha) & -\sin(\alpha) \\ 0 & \sin(\alpha) & \cos(\alpha) \end{pmatrix} \quad R_y(\beta) = \begin{pmatrix} \cos(\beta) & 0 & \sin(\beta) \\ 0 & 1 & 0 \\ -\sin(\beta) & 0 & \cos(\beta) \end{pmatrix}$$

$$R_z(\gamma) = \begin{pmatrix} \cos(\gamma) & -\sin(\gamma) & 0 \\ \sin(\gamma) & \cos(\gamma) & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

- Translation vector t

$$t = \begin{pmatrix} t_x \\ t_y \\ t_z \end{pmatrix}$$

Extended camera model



- Extrinsic parameters

- Offset camera to world coordinate, e.g. when using multiple cameras or a robot
- Transformation from world to camera coordinate system
- Defined through a coordinate transform consisting of
 - Rotation matrix R
 - Translation vector t

$$x_c = R \cdot x_w + t$$

- In homogenous coordinates:

$$\begin{pmatrix} x_c \\ 1 \end{pmatrix} = \begin{pmatrix} R & t \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x_w \\ 1 \end{pmatrix}$$

- Projection matrix P : 3x4 matrix containing both intrinsic and extrinsic parameters

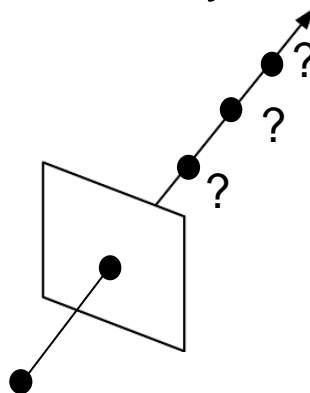
$$\begin{pmatrix} u \cdot w \\ v \cdot w \\ w \end{pmatrix} = P \begin{pmatrix} x \\ y \\ z \\ 1 \end{pmatrix} \quad P = (KR|Kt)$$

Which of the following is NOT contained in the projection matrix?

- A: Principal point
- B: Focal length
- C: Lens distortion parameters
- D: Translation to world coordinate system

Camera calibration

- Process of determining intrinsic and extrinsic parameters
- Intrinsic parameters should remain constant for different setups unless zoom or focus of a camera changes
- Extrinsic parameters are dependent on the selection of world coordinate system and change depending on setup
- Once calibrated, a function f is known that maps points in world coordinate system onto the image coordinate system $f: \mathbb{R}^3 \rightarrow \mathbb{R}^2$
- f is defined through the projection matrix P and normalizing of the homogenous coordinates
- The inverse function maps a point of the image coordinate system onto a straight line in world coordinate system that runs through the projection center



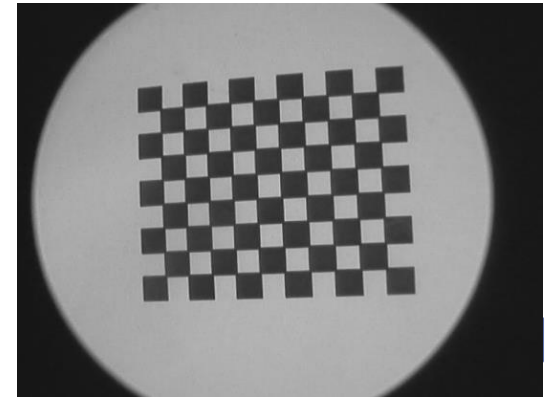
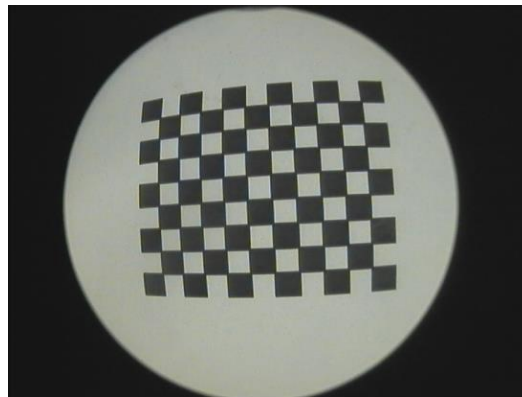
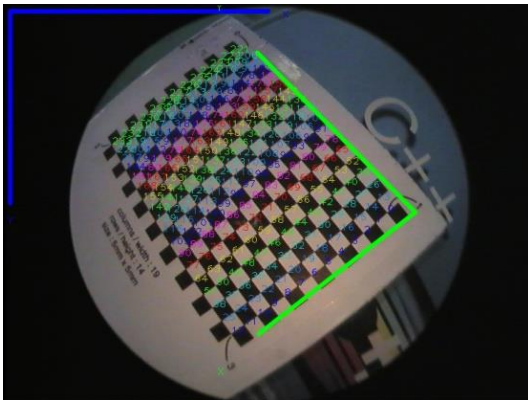
Camera calibration

Wanted:

P is a 3×4 -Matrix \Rightarrow 12 unknown variables

- Process *calibration*:

1. Locating a number of 3D/2D point correspondences
2. 3D points are known from usage of an appropriate calibration object or pattern
3. 2D points are located through computer vision methods
4. Estimation of P
5. Estimation of distortion parameters from backprojection error
6. Undistort 2D points and repeat from 4.



Direct Linear Transformation

- Standard method for computation of projection matrix P is the Direct Linear Transformation (DLT)

$$\begin{pmatrix} x \cdot w \\ y \cdot w \\ w \end{pmatrix} = P \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix} \quad P = (K \ R \mid K \mathbf{t}) = \begin{pmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{pmatrix}$$

$$\Rightarrow \begin{aligned} x &= \frac{p_1 X + p_2 Y + p_3 Z + p_4}{p_9 X + p_{10} Y + p_{11} Z + p_{12}} \\ y &= \frac{p_5 X + p_6 Y + p_7 Z + p_8}{p_9 X + p_{10} Y + p_{11} Z + p_{12}} \end{aligned} \quad \begin{array}{l} \text{One parameter can be normalized.} \\ \text{Usually } p_{12} = 1. \end{array}$$

Direct Linear Transformation

$$\Rightarrow \begin{aligned} p_1X + p_2Y + p_3Z + p_4 &= xp_9X + xp_{10}Y + xp_{11}Z + x \\ p_5X + p_6Y + p_7Z + p_8 &= yp_9X + yp_{10}Y + yp_{11}Z + y \end{aligned}$$

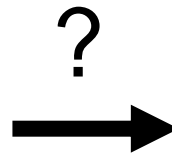
- Formulation as a linear system $A\mathbf{x} = \mathbf{b}$ with $n \geq 6$ point correspondences

$$A = \begin{pmatrix} X_1 & Y_1 & Z_1 & 1 & 0 & 0 & 0 & 0 & -x_1X_1 & -x_1Y_1 & -x_1Z_1 \\ 0 & 0 & 0 & 0 & X_1 & Y_1 & Z_1 & 1 & -y_1X_1 & -y_1Y_1 & -y_1Z_1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_n & Y_n & Z_n & 1 & 0 & 0 & 0 & 0 & -x_nX_n & -x_nY_n & -x_nZ_n \\ 0 & 0 & 0 & 0 & X_n & Y_n & Z_n & 1 & -y_nX_n & -y_nY_n & -y_nZ_n \end{pmatrix} \quad \mathbf{x} = \begin{pmatrix} p_1 \\ \vdots \\ p_{11} \end{pmatrix} \quad \mathbf{b} = \begin{pmatrix} x_1 \\ y_1 \\ \vdots \\ x_n \\ y_n \end{pmatrix}$$

3D cameras

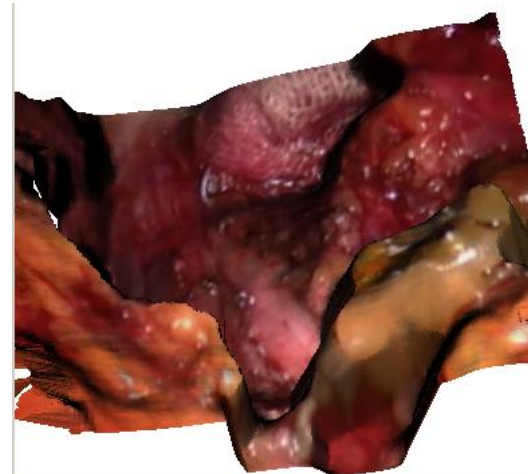
Until now: 2D vision

- Spatial information only secondary (experience)



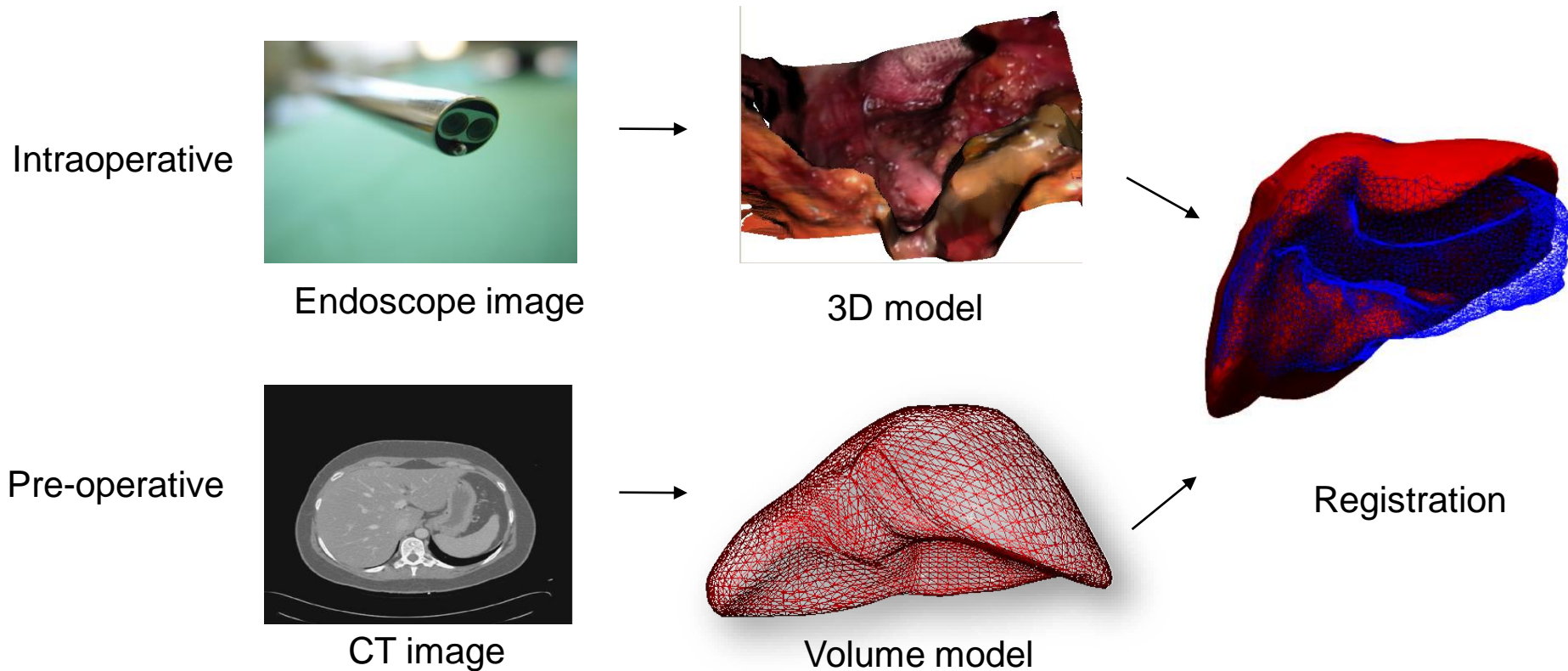
Goal: Computer-assistance via 3D model

- Navigation
- Augmented reality



3D endoscopy

- Goal: Navigation, augmented reality
 - Create intraoperative model with the endoscope
 - Registration with pre-operative model



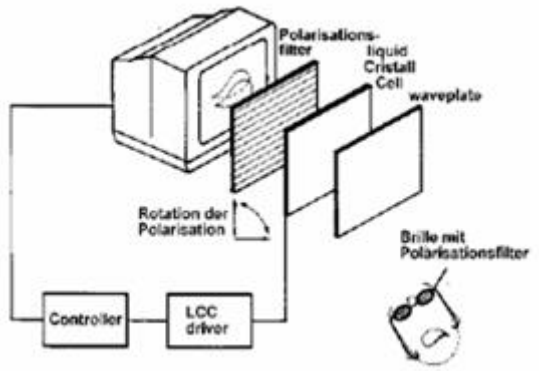
3D endoscopy

- **Applications without 3D reconstruction**
 - E.g. Shutter glasses
 - Accessories required (Glasses, ...)
- **Applications with 3D reconstruction**
 - Active or passive methods:
 - Stereo endoscopy
 - Structure from Motion
 - Time-of-Flight
 - Structured Light
 - Different endoscope types



Methods without 3D reconstruction

- No computer-support
- Depth perception is a result from the natural stereo vision of the viewer



Shutter glasser



3Scope HMD,
Trivisio Prototyping GmbH



da Vinci[®]
Surgical robot,
Intuitive Surgical, Inc.



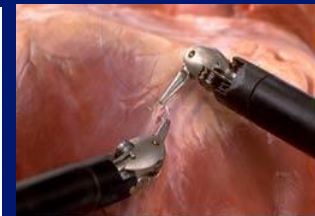
Quelle: Intuitive Surgical

DaVinci

Console



Manipulator

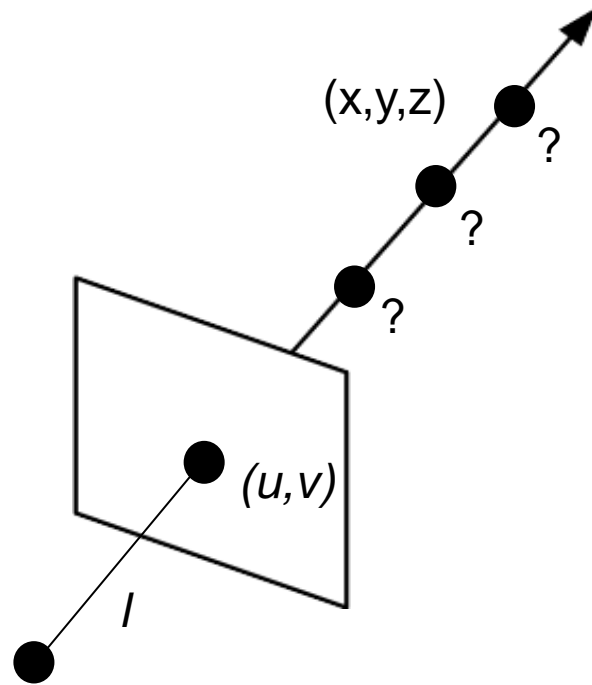


Quelle: Intuitive Surgical



2D to 3D

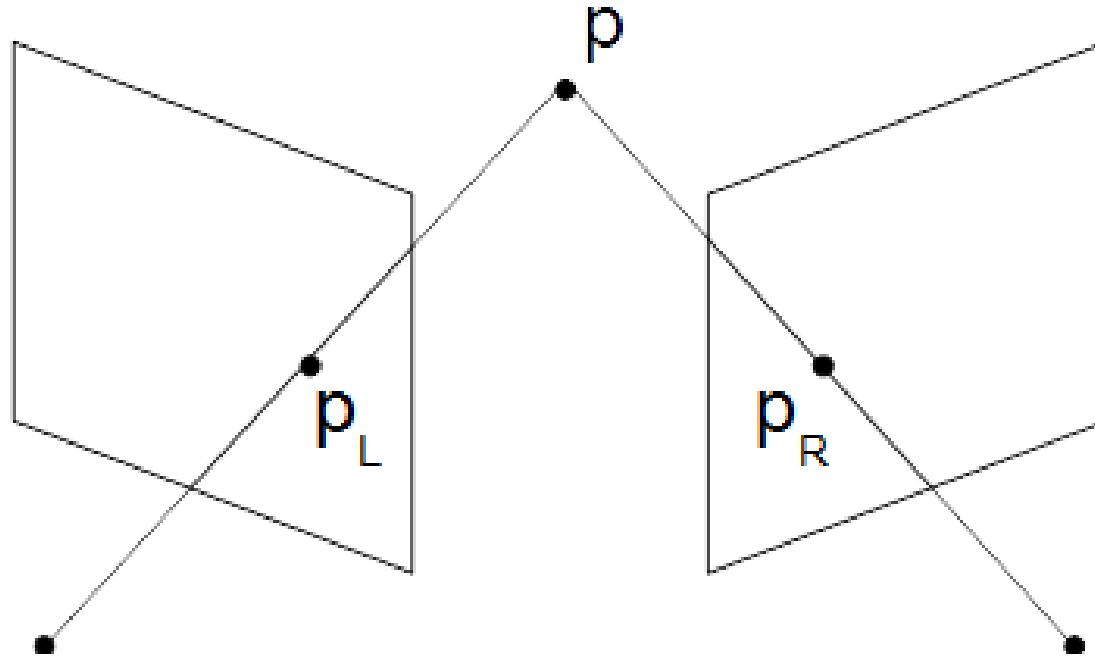
Given a 2D point, how do we reconstruct the original 3D point?



$$\begin{pmatrix} u \\ v \end{pmatrix} = R \cdot K \cdot \begin{pmatrix} x \\ y \\ z \end{pmatrix} + t \quad \Rightarrow \quad l: \lambda \cdot (R^{-1}K^{-1} \begin{pmatrix} u \\ v \end{pmatrix}) - R^{-1}t$$

λ variable describing position on line l

Stereo camera system - Triangulation



Given two calibrated cameras, each containing a projection (p_1, p_2) of point p , two lines can be computed:

$$l_L(\lambda_L) = \lambda_L \cdot (R_L^{-1}K_L^{-1}) - R_L^{-1}t_L$$

$$l_R(\lambda_R) = \lambda_R \cdot (R_R^{-1}K_R^{-1}) - R_R^{-1}t_R$$

Solve for λ_L, λ_R so that $l_L(\lambda_L) = l_R(\lambda_R)$, reconstructing point p

Stereo endoscopy

Used endoscope:

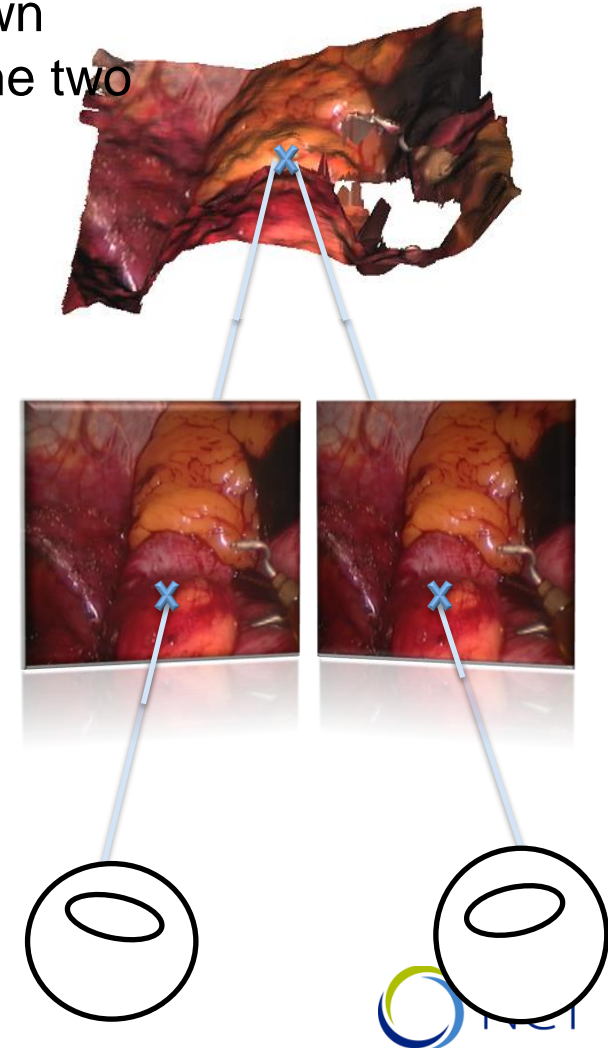
Stereo endoscope (two channels)

Reconstruction:

Triangulation with known relationship between the two cameras

Pro: known stereoscopic basis

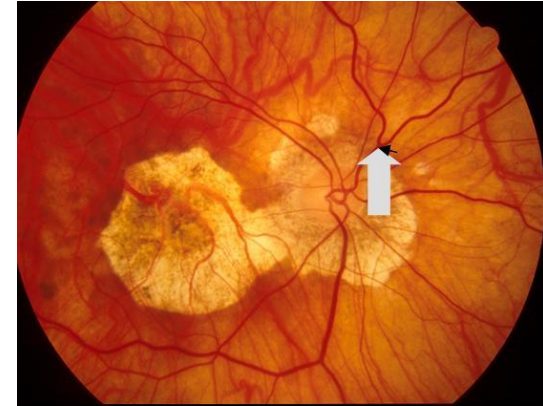
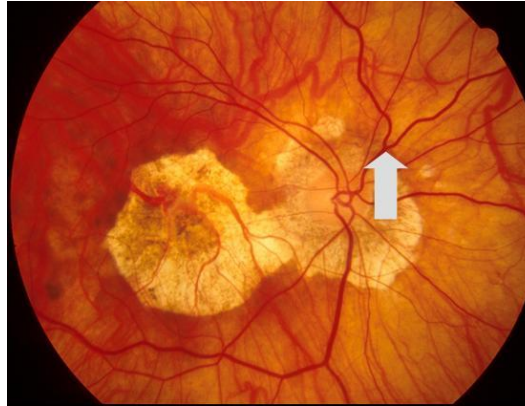
Cons: greater diameter
more expensive endoscope



Problem Stereo

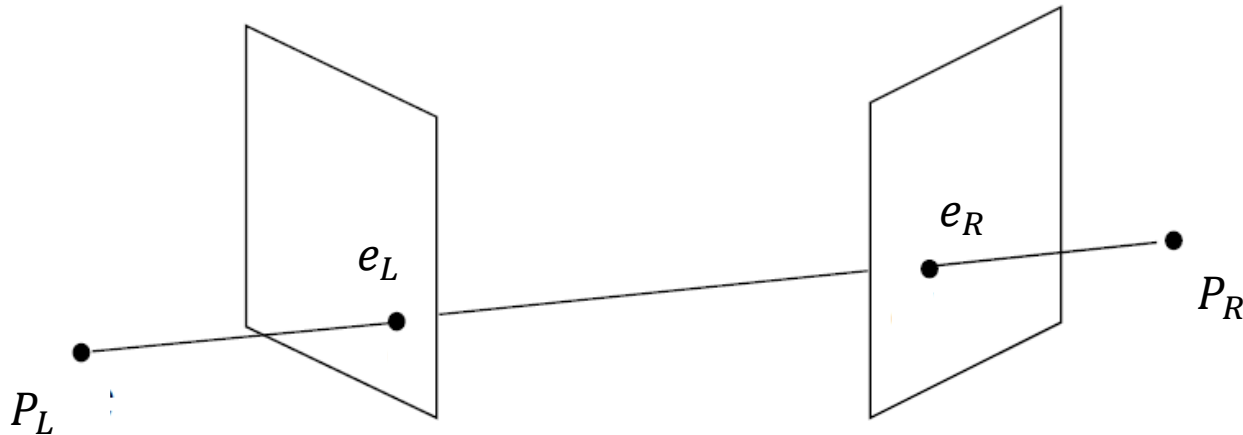
- Correspondence:

Which point in the left image belongs to which point in the right image?



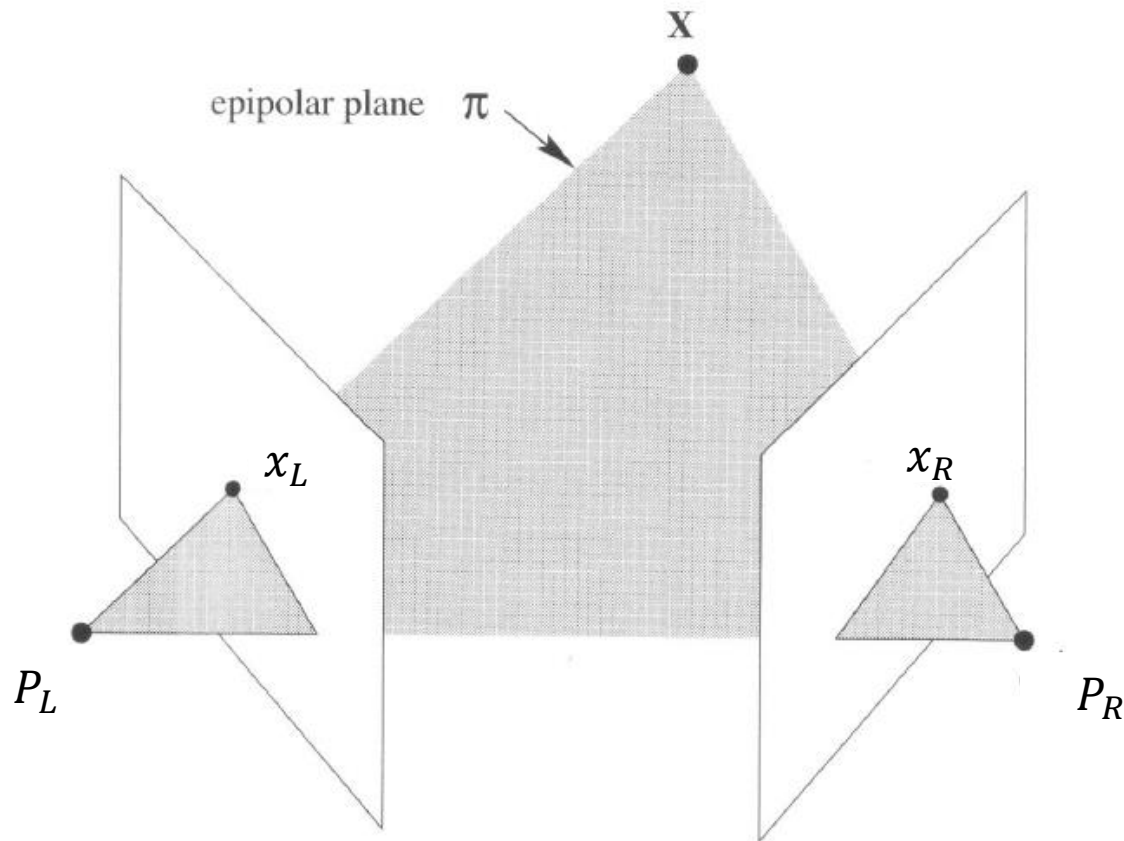
Epipolar geometry

- Relationship between two cameras is described through *Epipolar geometry*
- The points of intersection, e_L, e_R , of the line between the projection centers, P_L, P_R , are called *epipoles*



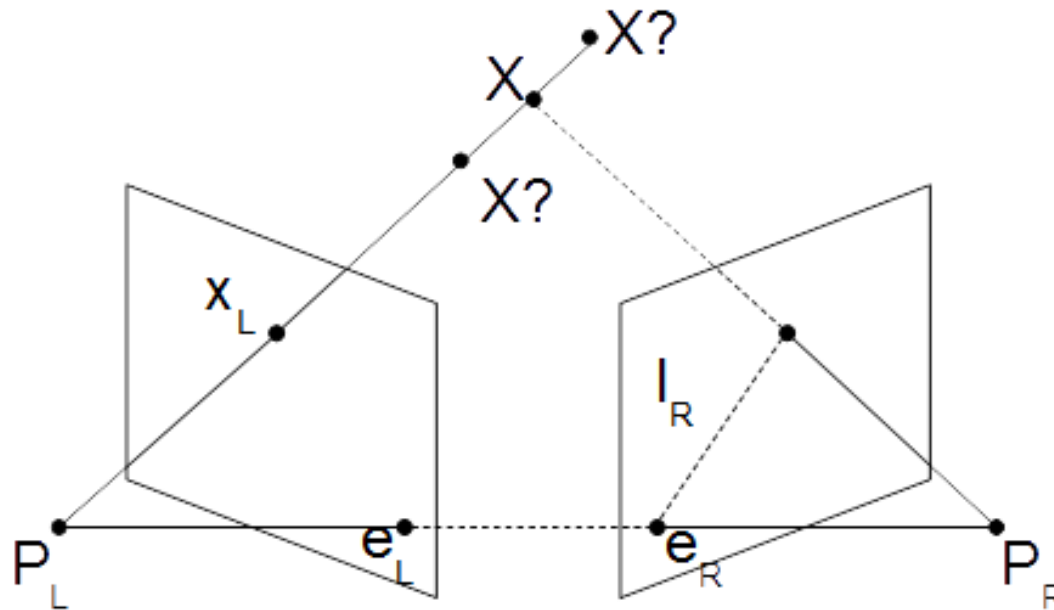
Epipolar geometry

- *Epipolar plane $\pi(X)$* :
 - Plane created through a 3D point X in the scene and the two projection centers P_L, P_R



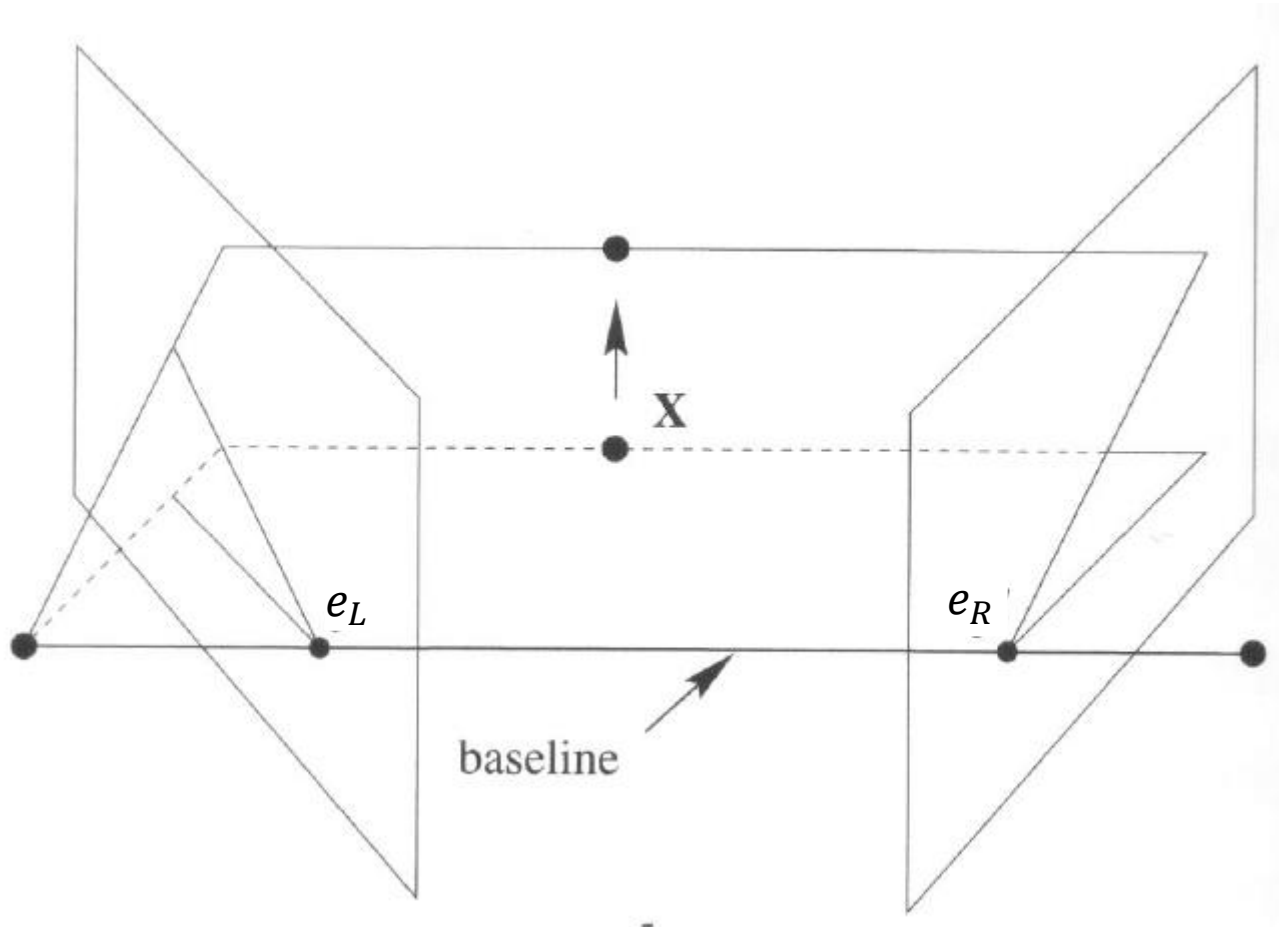
Epipolar geometry

- *Epipolar line* $l_R(x_L)$: line of intersection of $\pi(X)$ and image plane
- All 3D points X that could be projected onto x_L in the left image, are mapped onto a line $l_R(x_L)$ in the right image



Epipolar geometry

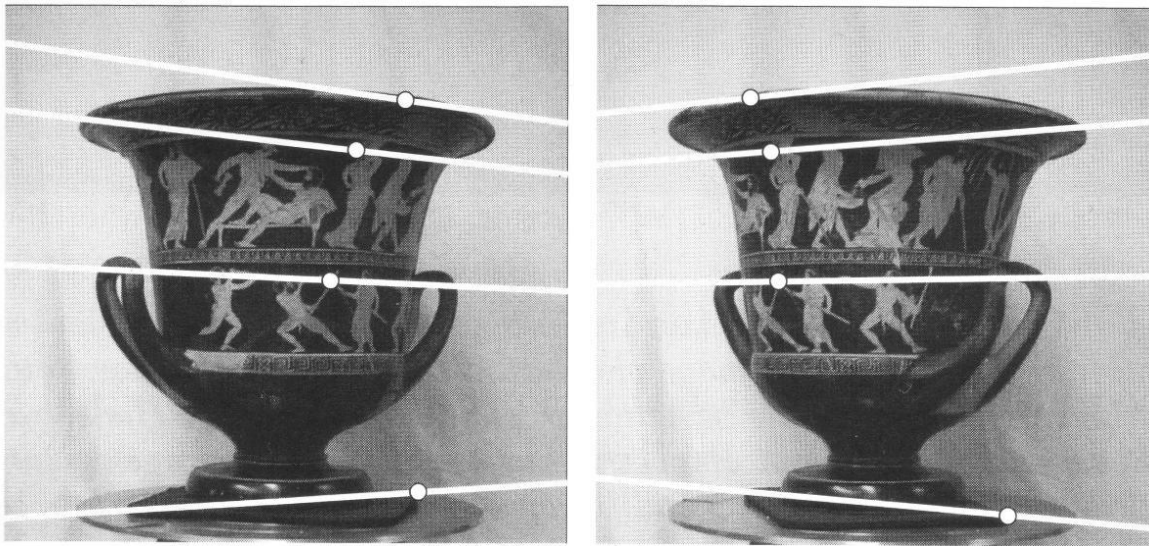
- All epipolar lines of a stereo camera system intersect in the epipoles e_L, e_R



Epipolar geometry

Usage:

- Reduction of the correspondence problem from two dimensions onto one dimension, as only points on an epipolar line have to be considered:
 - Higher robustness (less wrong correspondences)
 - Higher efficiency



Quelle: Multiple View Geometry

Fundamental matrix

- Mathematical description of the epipolar geometrie
- Properties of the Fundamental matrix F
 - 3x3 matrix
 - Has rank of 2
 - For all corresponding points x_L, x_R :
 - $x_L^T F x_R = 0$ (x_L, x_R are image points in homogenous form with $w = 1$)

Fundamental matrix

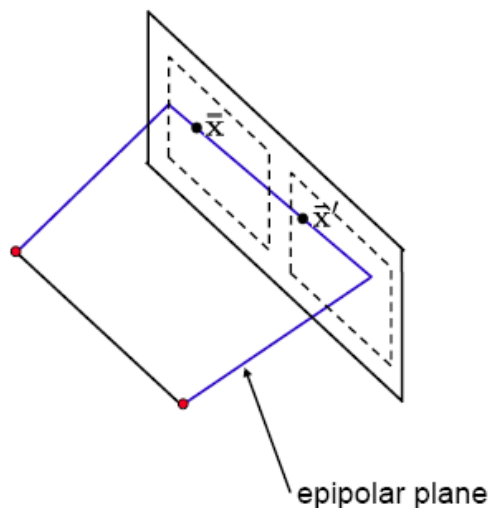
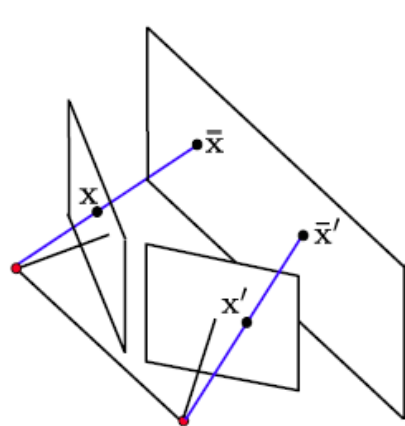
- Can be used to compute epipolar lines:
 - $l_L(x_R) = F^T x_R$
 - $l_R(x_L) = F x_L$
- For the epipoles:
 - $F^T e_R = 0$
 - $F e_L = 0$
- l_L (l_R analog) describes a 2D line in the following manner:
 - $l_L x = 0$ for all x (in homogenous form with $w = 1$) that lie on this line
- Fundamental matrix can be compute in multiple ways
 - Using known image correspondences in the left and right images
 - When intrinsic and extrinsic parameters are known, directly using K_L and K_R and the Essential matrix E , which contains the extrinsic parameters

Fundamental matrix

- Computation with known intrinsic and extrinsic parameters
 - Assumption extrinsic parameters
 - Left camera ($I|0$) as transformation, i.e. identity
 - Right camera ($R|t$) as transformation
 - Essential matrix E can be computed in the following manner:
 - $$E = [t]_x \cdot R = \begin{pmatrix} 0 & -t_z & t_y \\ t_z & 0 & -t_x \\ -t_y & t_x & 0 \end{pmatrix} R$$
 - Fundamental matrix F can then be composed:
 - $$F = K_R^{-T} \cdot E \cdot K_L^{-1}$$
- If the Fundamental matrix has been computed from point correspondences and the intrinsic parameters are known, the Essential matrix can be computed:
 - $$E = K_R^T \cdot F \cdot K_L$$

Rectification

- If the epipolar geometry is known, images can be rectified:
 - Epipolar lines are parallel to the horizontal axis in a rectified image pair
 - Search for correspondences is restricted on a horizontal direction
 - Corresponding points share same y-coordinate, difference in x-coordinate is called disparity d



Rectification

- Rectified images have the benefit that optimized algorithms for correlation can be used to find correspondences
- Cons:
 - Interpolation necessary for rectifying images
 - ⇒ Loss in quality
 - Depending on setup, images can be highly distorted

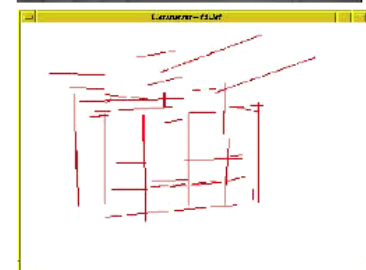
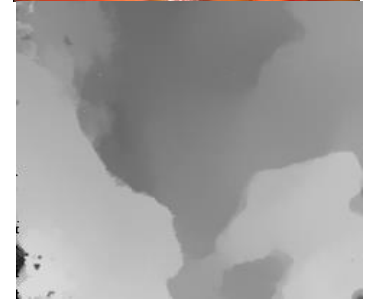
Rectification

Which statement is incorrect?

- A: only possible with calibration
- B: reduces image quality
- C: improves runtime
- D: reduces dimensionality during correspondence analysis

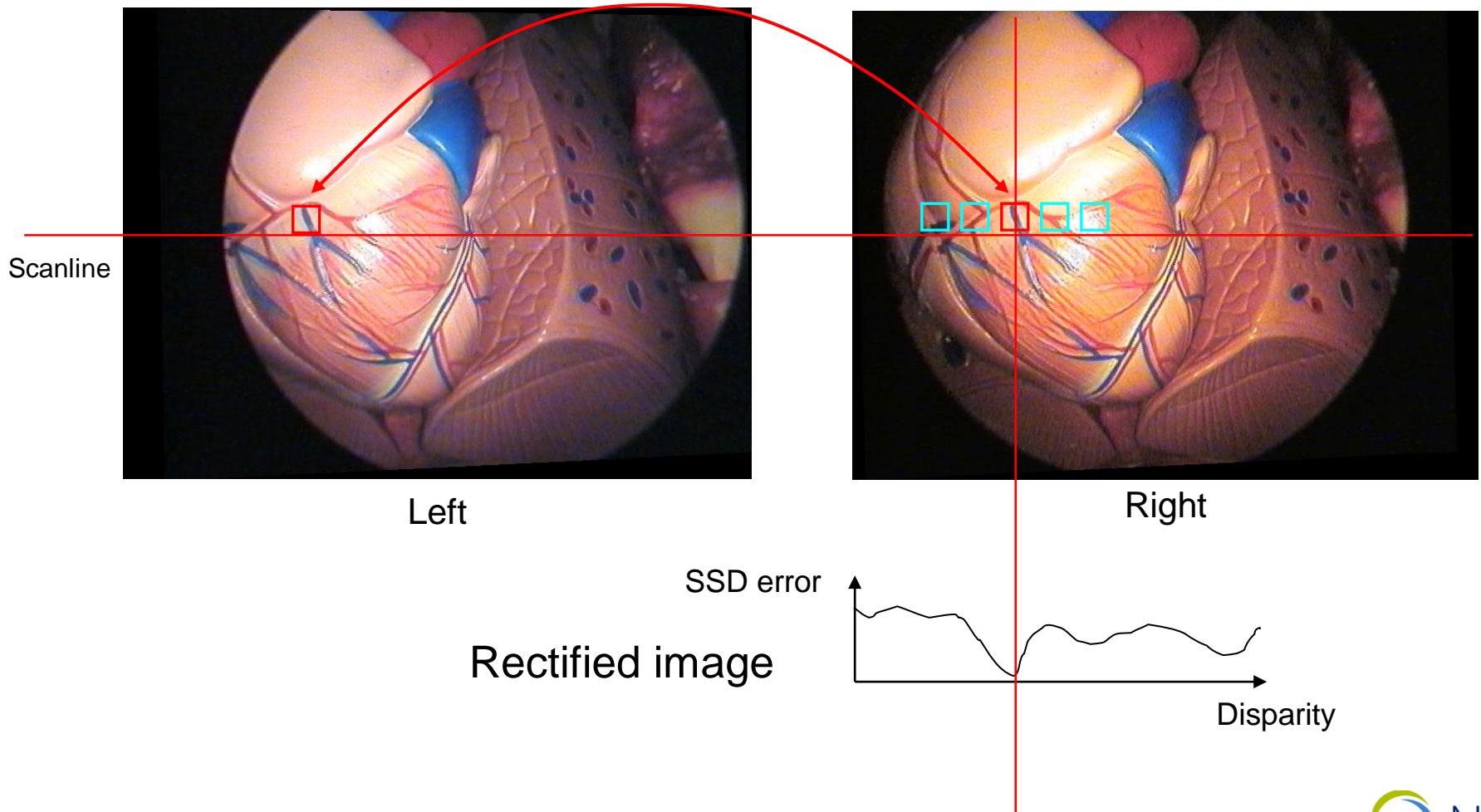
Correspondence analysis

- Classification into 2 types:
 - Correlation-based approaches
 - Correspondence for each pixel
 - Dense depth map
 - Application: Textured scene
 - Feature-based approaches:
 - Correspondence only for certain features
 - Sparse depth map
 - Application: Structured scene (Indoor)



Correspondences via correlation

- Corresponding elements are image windows
- Correlation as similarity measure



Normalization

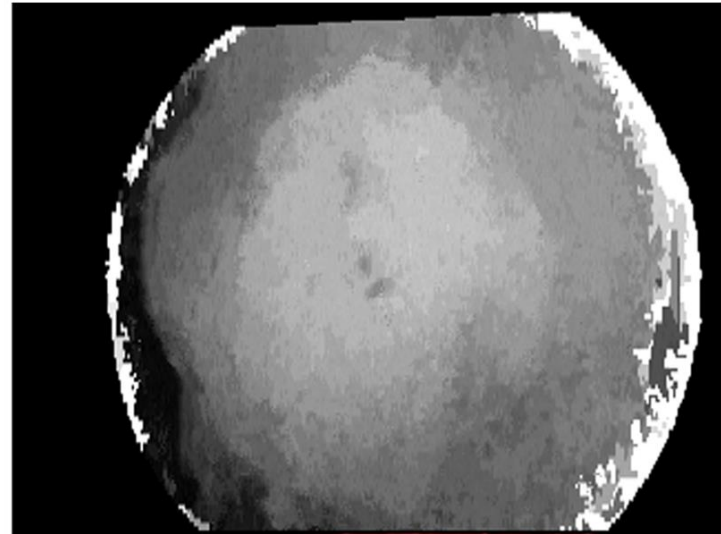
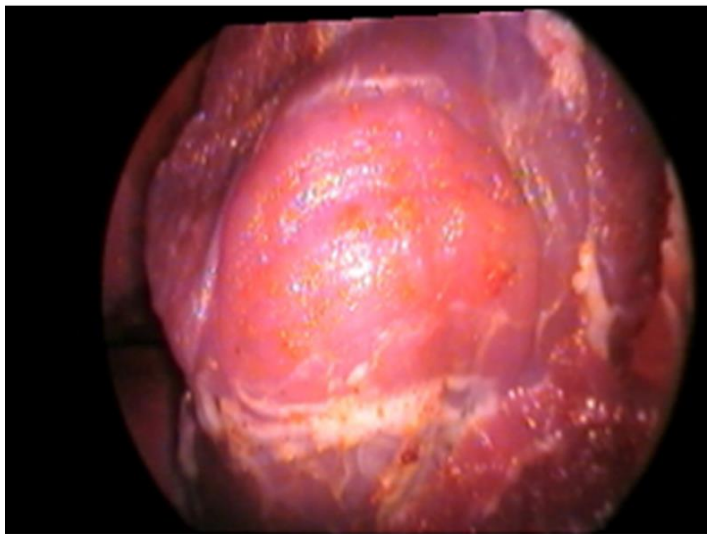
- Images from different cameras can vary due to varying lighting conditions
 - Differing sensitivity of the sensors
- Normalization of pixels in each search window

$$\bar{I} = \frac{1}{|W_m(x, y)|} \sum_{(u, v) \in W_m(x, y)} I(u, v) \quad \text{Average}$$

$$\|I\|_{W_m(x, y)} = \sqrt{\sum_{(u, v) \in W_m(x, y)} [I(u, v)]^2} \quad \text{Magnitude}$$

$$\hat{I}(x, y) = \frac{I(x, y) - \bar{I}}{\|I - \bar{I}\|_{W_m(x, y)}} \quad \text{Normalization}$$

Disparity maps



Disparity map

A dark pixel in the disparity map implies:

- A: Point close to the camera
- B: Point far from the camera
- C: Point not defined
- D: Point has many correspondences

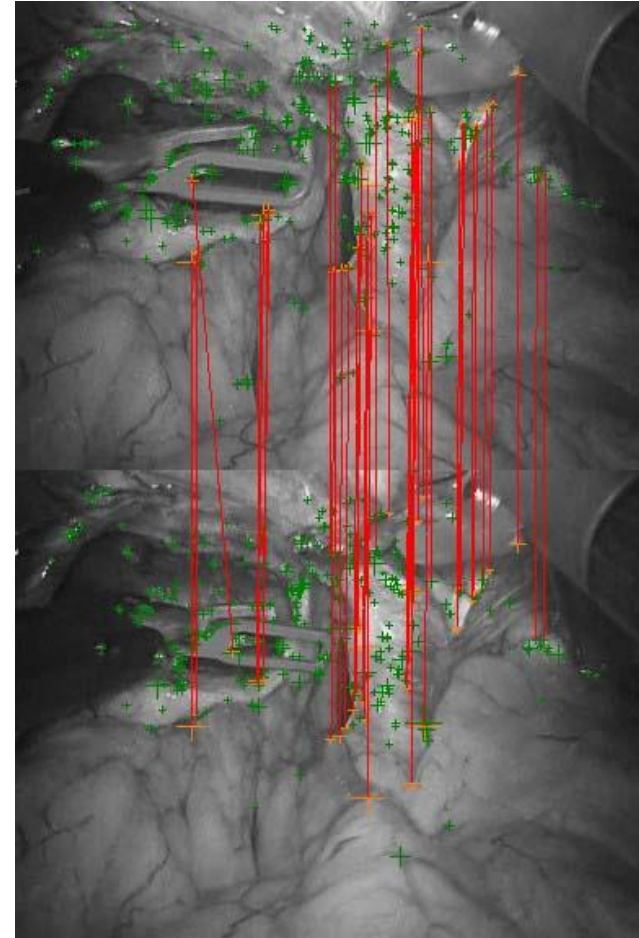
Disparity map

A dark pixel in the disparity map implies:

- A: Point close to the camera
- **B: Point far from the camera**
- *C: Point not defined (when completely black)*
- D: Point has many correspondences

Correspondences via features

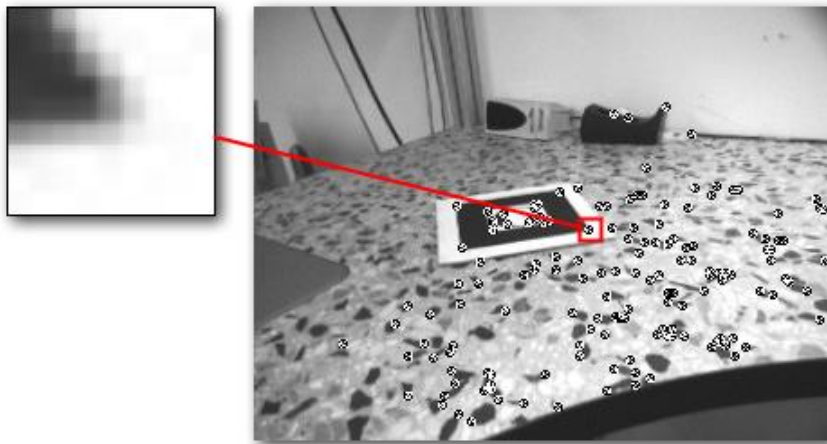
- Search restricted to few local point features
- Properties:
 - No occlusions, reproducible in different views, can be re-detected
 - Invariant against: Scaling, rotation, lighting
 - Neighborhood contains information
- Pixel feature: $(2n+1) \times (2n+1)$ -Pixel-Block around Pixel p
- Computation is divided into detection and descriptor



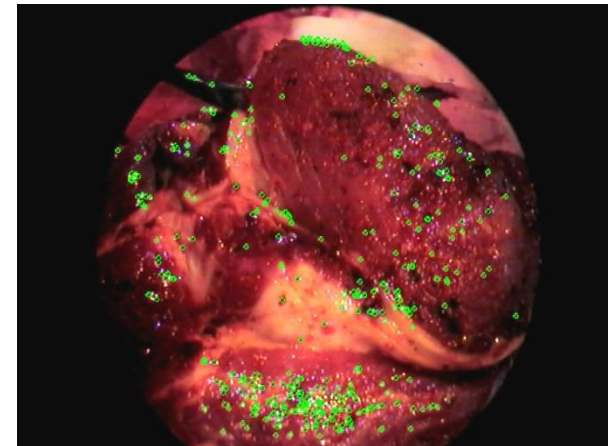
Correspondences via features

- Detection: Locating stable, transformation invariant key points
- Depending on the algorithm due points different in localization, scale and structure
- Descriptor: Robust, unique characterization of the local neighborhood, e.g. through gradient information or frequency spectrum
- Examples:

Harris Corner Detector



SIFT-Detector



Correspondences via features

Example: **Harris-Corner-Detector** :

If the Eigenvalues of the matrix

$$A = \begin{pmatrix} \left(\frac{\partial \text{Img}(x,y)}{\partial x} \right)^2 & \frac{\partial \text{Img}(x,y)}{\partial x} \frac{\partial \text{Img}(x,y)}{\partial y} \\ \frac{\partial \text{Img}(x,y)}{\partial x} \frac{\partial \text{Img}(x,y)}{\partial y} & \left(\frac{\partial \text{Img}(x,y)}{\partial y} \right)^2 \end{pmatrix}$$

are large, a small step in any direction will cause a large change in gray value.

Finding corner through looking for local maxima in:

$$R = \det A - k \cdot \text{trace}(A)^2, k \approx 0.04$$

Problems/Comparison

- Problems:
 - Occlusion
 - Limited field of view
 - Specularities, changes in light conditions
 - Surface structure: Sparse texture / repeating texture
- Comparison:

Correlation-based

Dense depth map

Only for textured scenes

Prone to errors from changes in direction

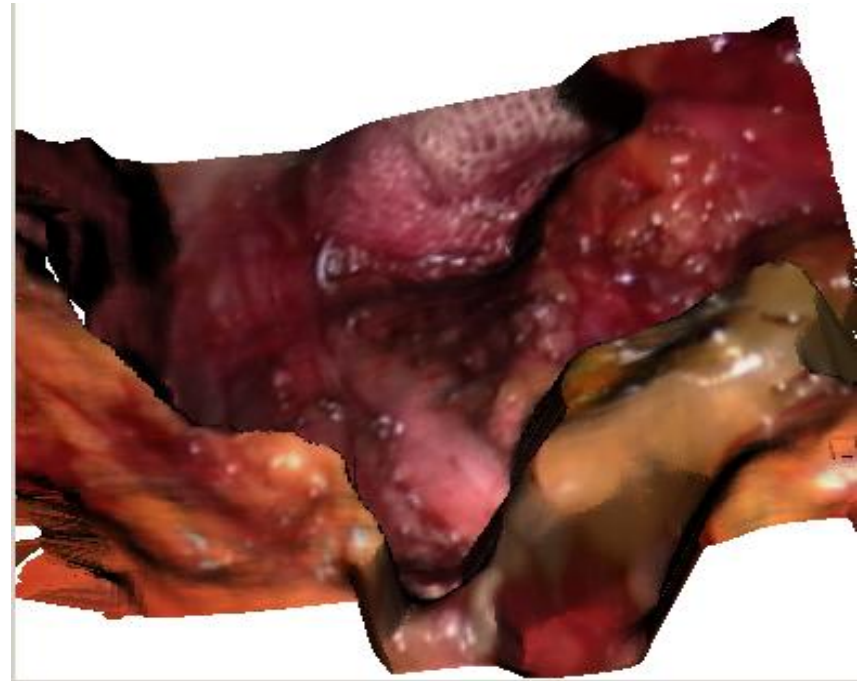
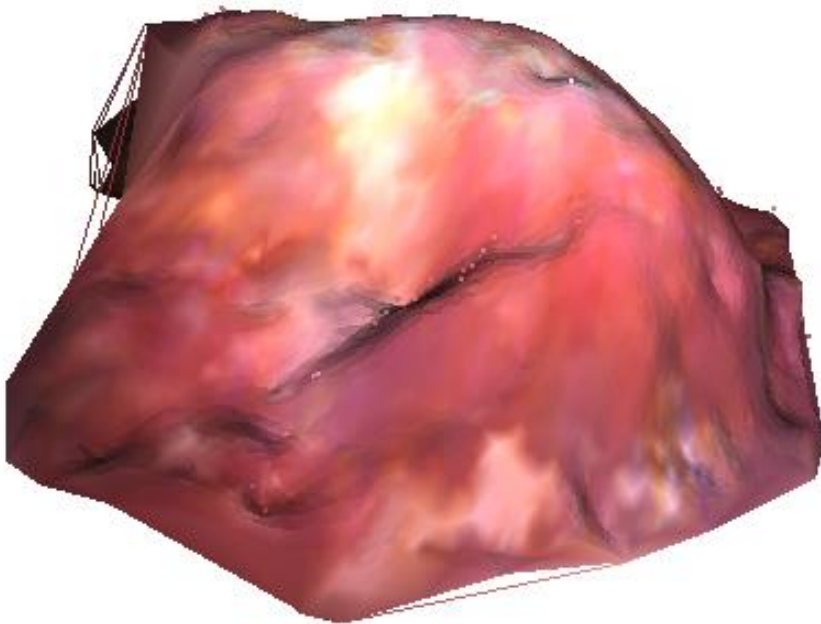
Feature-based

Sparse depth map

Prone to errors from wrong correspondences

Specific pros and cons have to be weighted for each use case

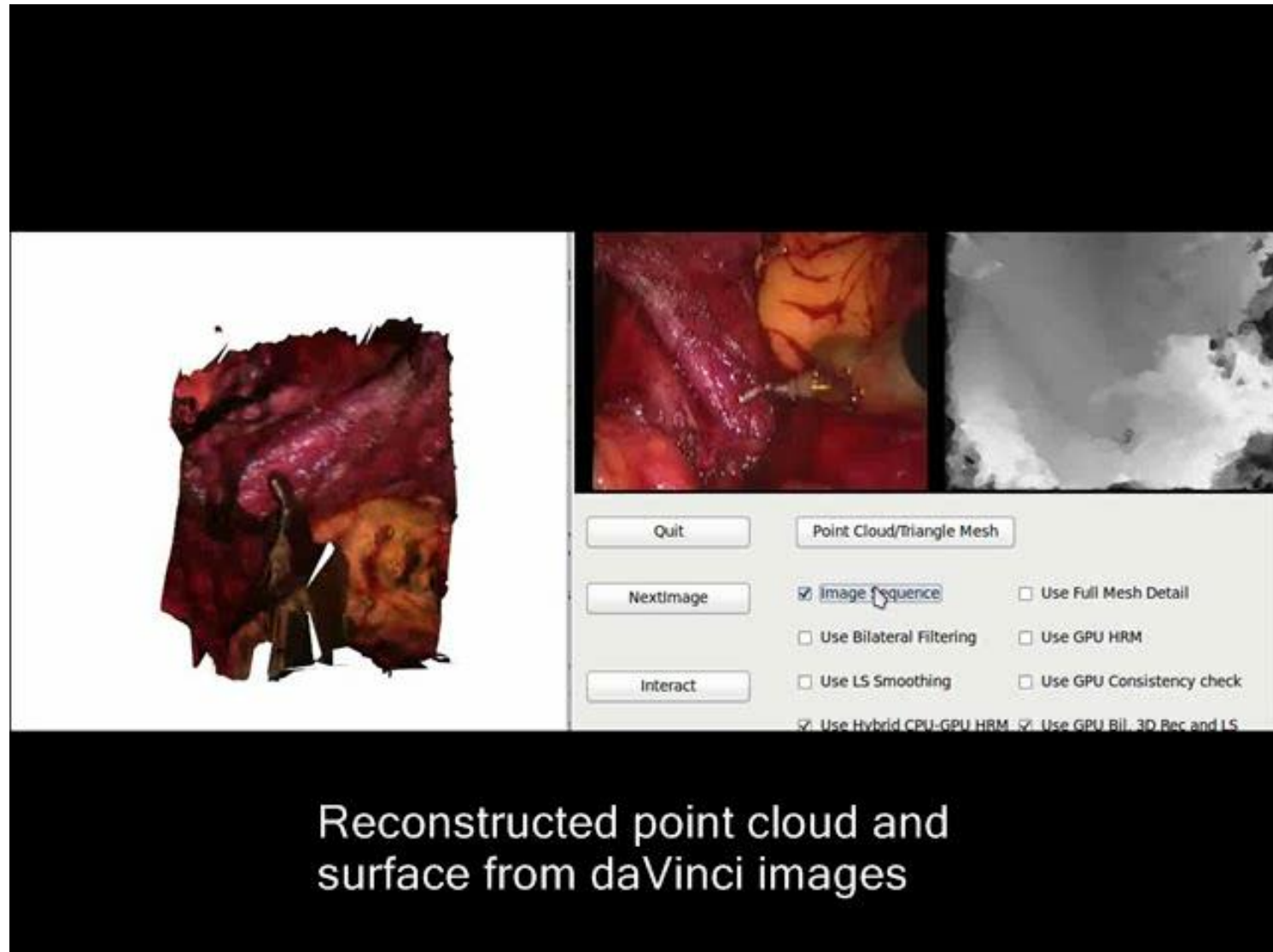
3D-model



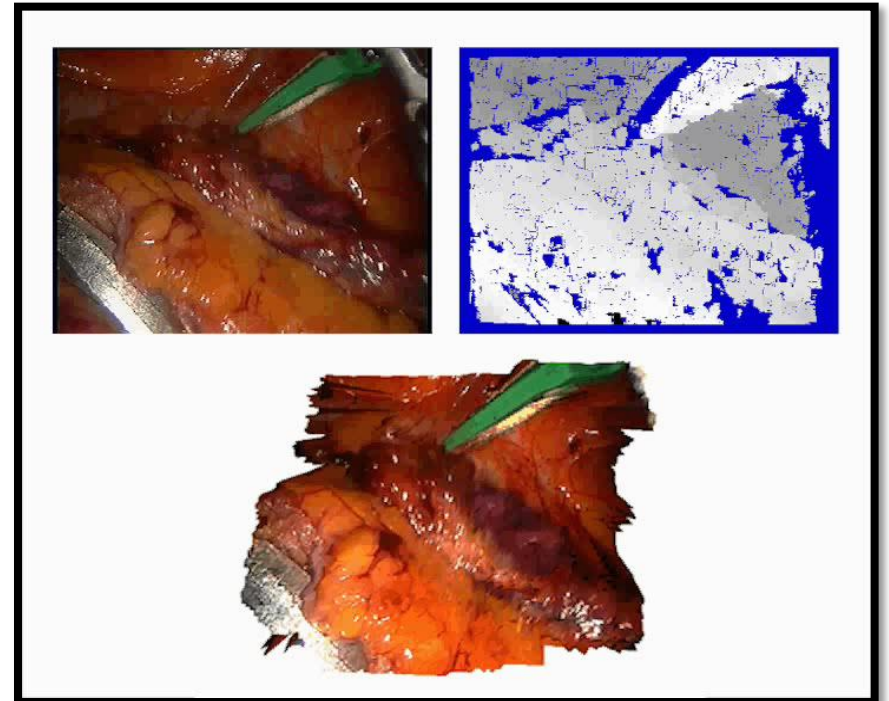
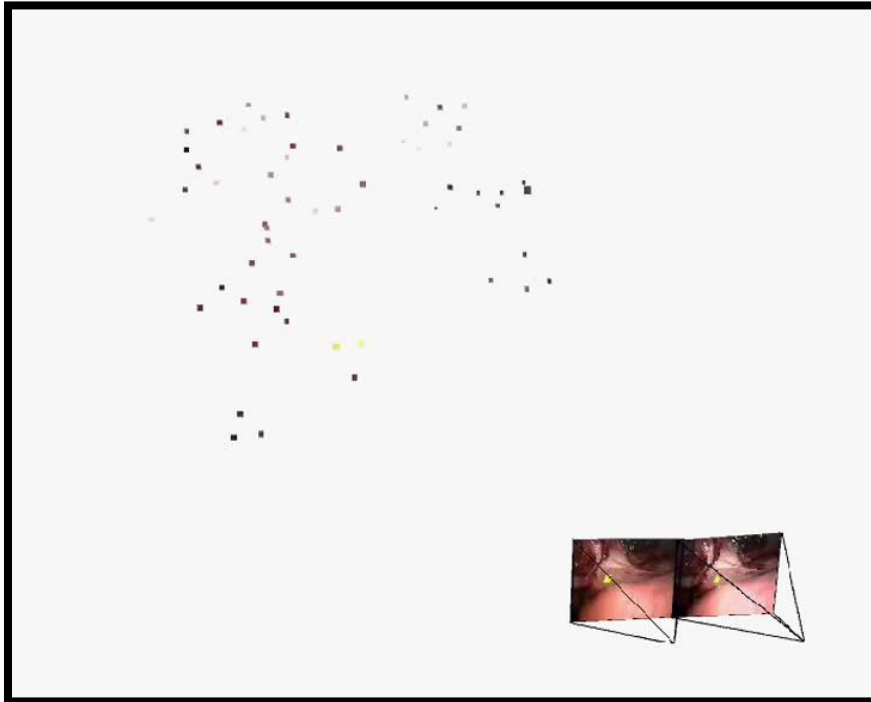
Stereo endoscopy

- Given:
 - two calibrated cameras
(Projection matrices given)
- 3D-Reconstruction:
 - Rectification
 - Correspondence search:
 - Correlation-based or feature-based
 - Optional: Left/Right check
 - Optional: Detection of wrong correspondences
 - Triangulation
- Net generation
 - Texturizing of net

Stereo endoscopy



Stereo endoscopy



Stoyanov *et al.*: "Real-time Stereo Reconstruction in Robotic Assisted Minimally Invasive Surgery", MICCAI 2010

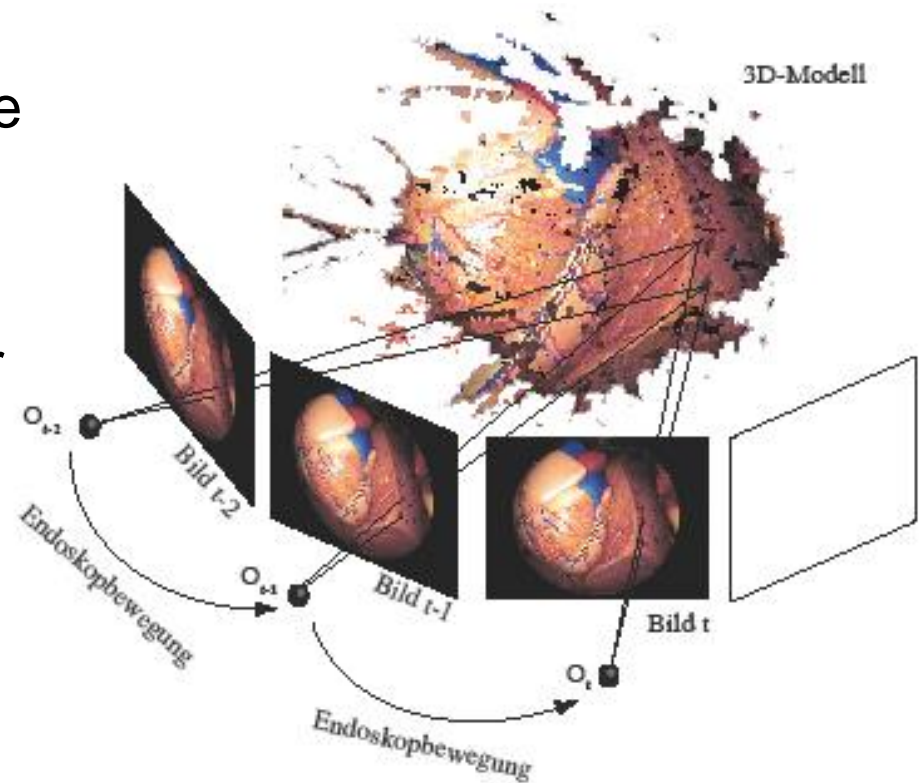
Stereo endoscopy - Evaluation

- Pros
 - High accuracy with good correspondences
 - No additional hardware (e.g. Tracking system, special light source) besides camera necessary
 - Dense depth map with correlation-based approaches
- Cons
 - Expensive hardware
 - Accuracy decreases with lower distances between cameras
 - Very accurate calibration necessary
 - For feature-based approaches:
 - Potentially fewer points on surface
 - Prone to wrong correspondences
 - Occlusions, shadows
 - Problems through weakly textured surface, smoke, blood, etc.

Structure-from-Motion

Problem:

- One channel endoscope
- Computation of scene structure and camera movement from images
- Image either simultaneously or sequential, scenes are geometrically equivalent
 - Position of camera not know: has to be estimated from correspondences



Motion Compensated SLAM (MC-SLAM)

Quelle: Moutney, Imperial College

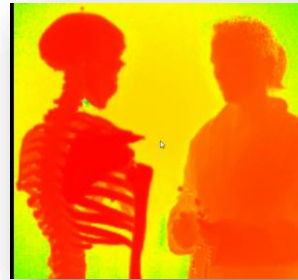
Structure from Motion - Evaluation

- Pros
 - High accuracy with good correspondences
 - Relative low hardware cost in comparison to other methods
- Cons
 - Potentially few features
 - Prone to correspondence errors
 - Occlusions, shadows
 - Problems from sparsely textured surfaces, specularities, smoke etc.
 - Often requires tracking
 - Difficult with fast moving objects

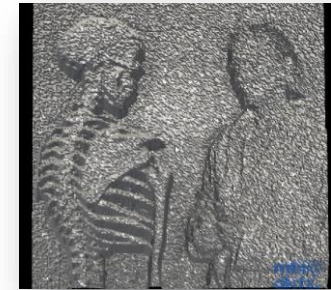
Further methods: Time-of-Flight



Time-of-Flight (ToF) Camera



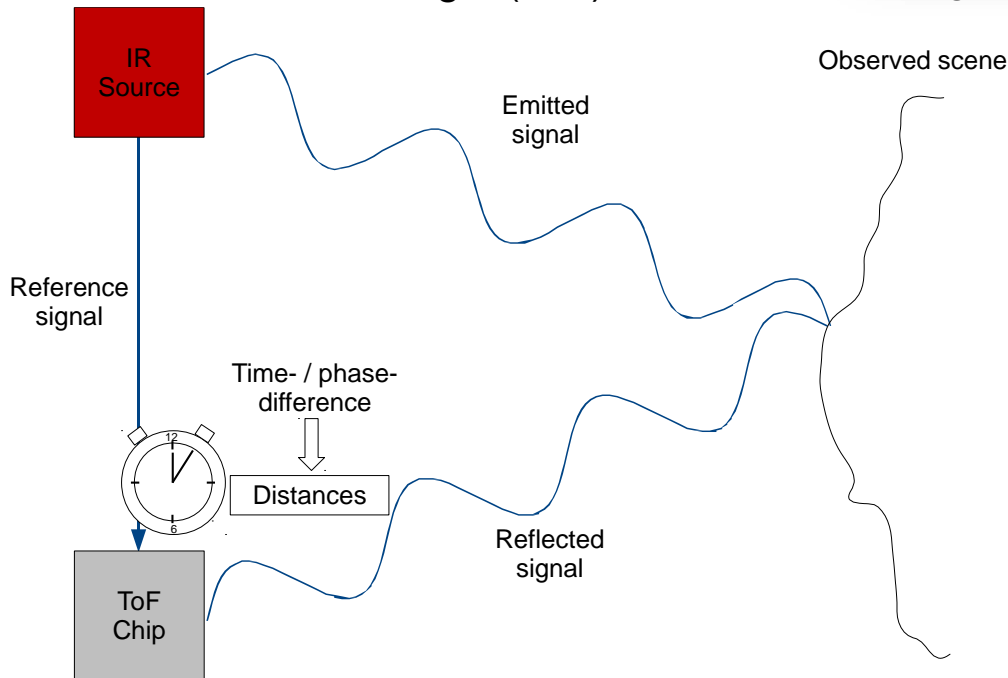
Range image



Surface



Quelle: Seitel, Maier-Hein, DKFZ

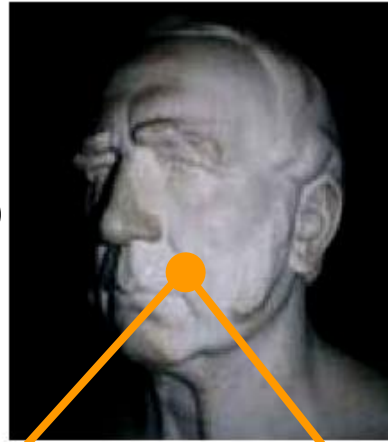


ToF - Evaluation

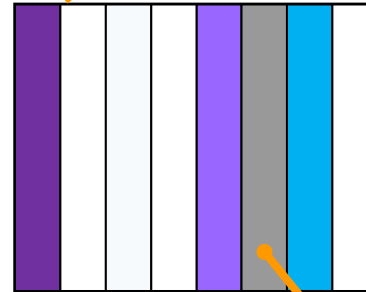
- Pros
 - No features required
 - Dense depth map
 - No shadow effects
 - No image processing necessary
- Cons
 - No color image
 - Low resolution
 - Systematic errors
 - Can't deal with transparent structures

Further methods: Structured light

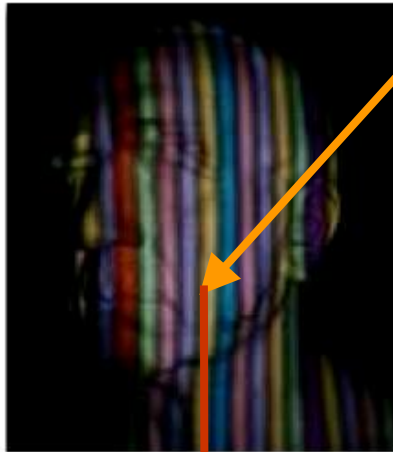
- Through projection of a known pattern, we can draw conclusion on an objects 3D shape



Pattern



Example
frequency coding



Color identifies the stripe



Structured light - Evaluation

- Pro
 - No need to rely on features
 - Density of correspondence selectable
 - Less complex correspondence search
 - Works well for homogenous surfaces
- Cons
 - Additional hardware
 - Projected light can be bothersome
 - Sensitive against reflections and transparencies
 - Difficult: Segmentation of symbols/correct detection of color values

Literature

- Trucco, Verri: “Introductory Techniques for 3D Computer Vision”
- Hartley, Zisserman: “Multiple View Geometry”
- Vogt. et al.: “Bildverarbeitung in der Endoskopie des Bauchraums”. BVM 2001
- Zimmerman et al.: “Automatic Detection of Specular Reflections in Uterine Cervix Images“. SPIE Medical Imaging 2006
- Wengert et al.: „Markerless Endoscopic Registration and Referencing“. MICCAI 2006
- Stoyanov et al.: “Soft-Tissue Motion Tracking and Structure Estimation for Robotic Assisted MIS Procedures“. MICCAI 2005
- Mountney et al.: Motion Compensated SLAM (MC-SLAM) for Image Guided Surgery
- Dillmann et al.: Lecture Robotik III, KIT