Capturing and Modelling 3D Data

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Some research objectives

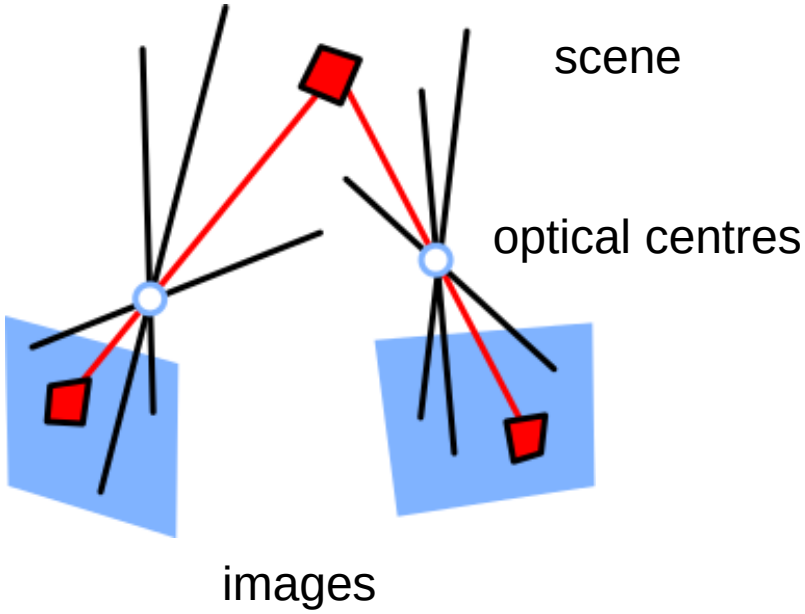
- Reconstruct 3D scenes from images
- Model 3D scene-statistics
- Understand human binocular vision
- Applications:
  - View synthesis, augmented reality
  - Re-rendering for 3D displays
  - Active robot vision

Intelligent Sensing

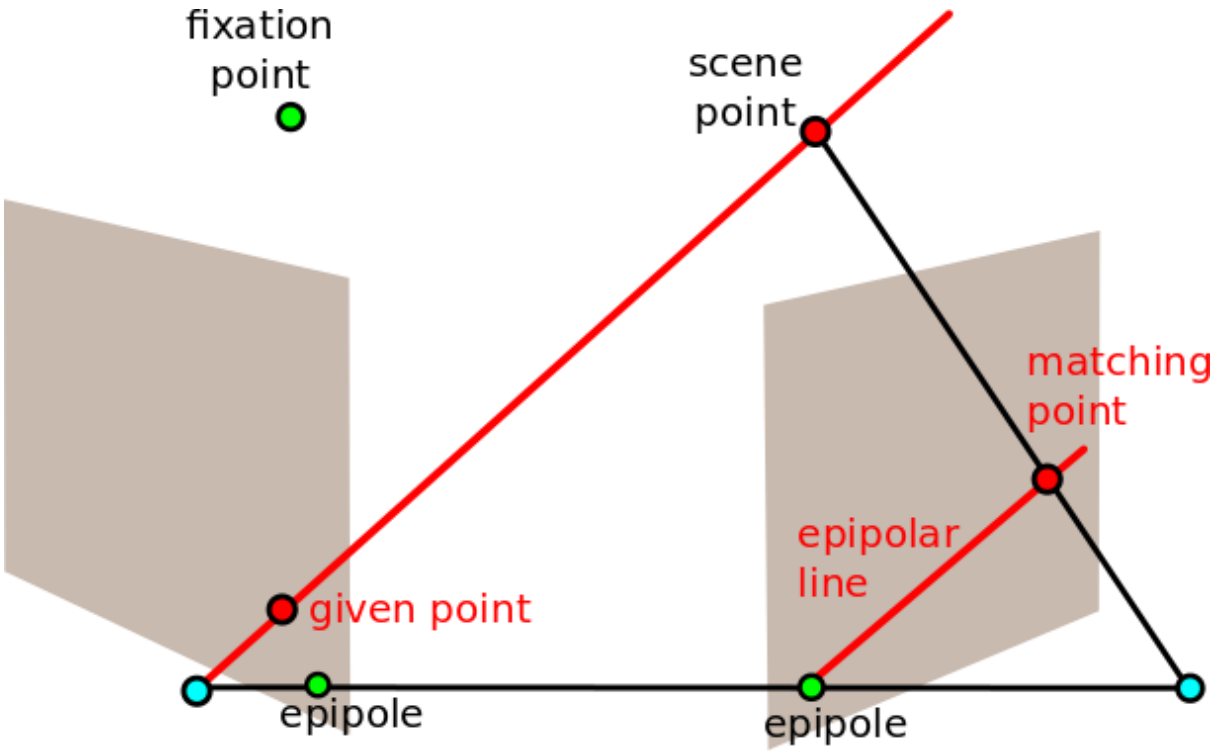
- Intelligent sensors should interact with the environment
- Adjust camera positions in relation to scene (active vision, SLAM)
- Actively probe the scene (structured light, time-of-flight)
- Would help to have a prior statistical model of the scene
- Examples of these strategies can be found in animals

Parallax-based 3D reconstruction

- Traditional method, e.g. depth from binocular disparity
- Cameras must be calibrated
- Main problems are mismatched / unmatched regions
- Can use the same images (textures) for rendering



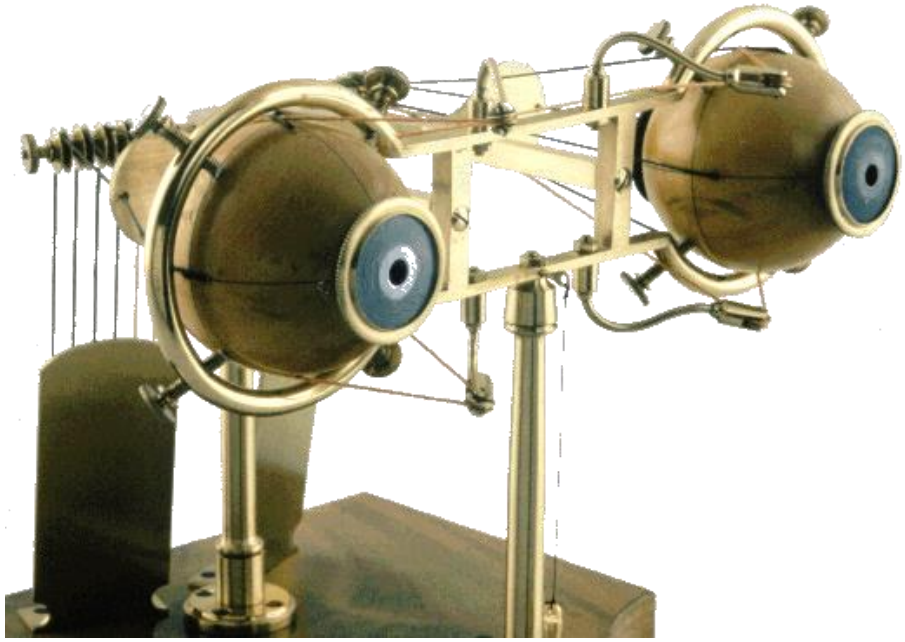
Epipolar geometry



- Epipolar line in one image ↔ ray through other image
- Search for correspondences is limited to 1D

Human binocular vision

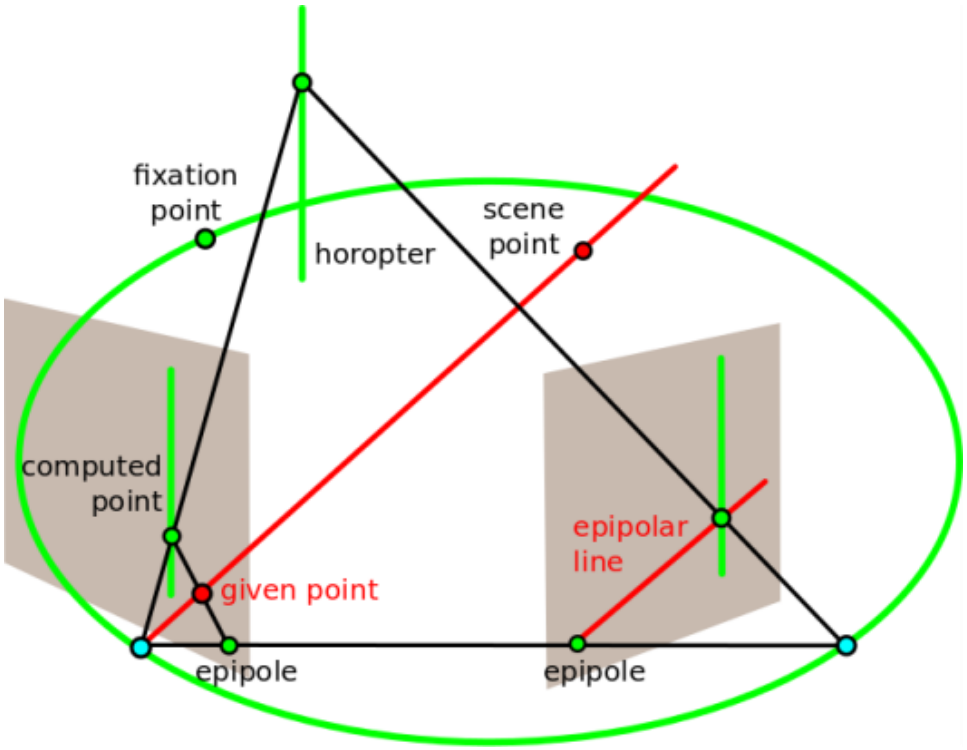
- Eye-movements are highly coordinated
- There is always an (approximate) 3D fixation-point
- Listing's Law determines the torsion of the eyes



Advantages of active stereo

- Accuracy of depth estimation can be improved
- Calibration problem is simplified
- Some extra depth cues (e.g. vergence)
- Search for corresponding points is reduced
  - Most features around the fixation-point have small disparity
  - Assuming that the 3D world is piecewise-smooth
- Not used by all animals (e.g. owls)

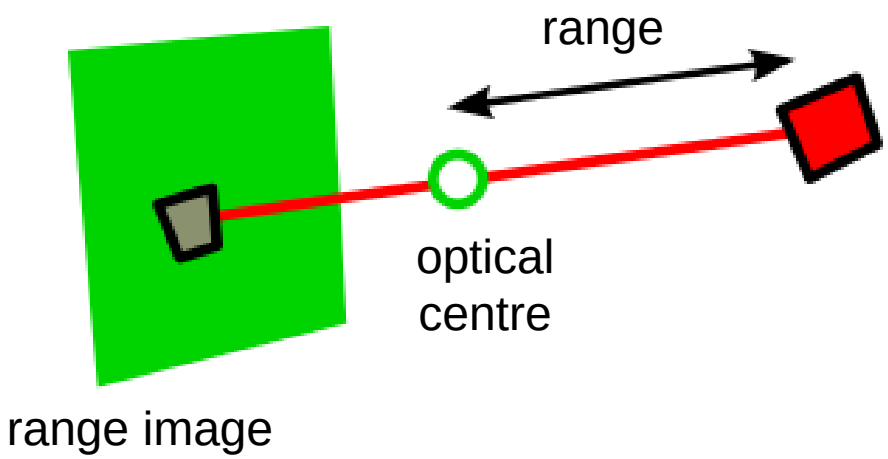
Fixation and epipolar geometry



- Horopter projects identically in the images
- Has the 3D form of a circle+line in fixating case
- A good parameterization of epipolar geometry (F matrix)

Time-of-flight (TOF) cameras

- Active depth-sensing devices (infrared)
- Optically similar to a camera (lens, CCD, etc)
- Estimates *distance* to scene along each ray
- Works by measuring phase delay of pulsed-light
- Very low spatial resolution (e.g. 176 × 144)
- No colour!



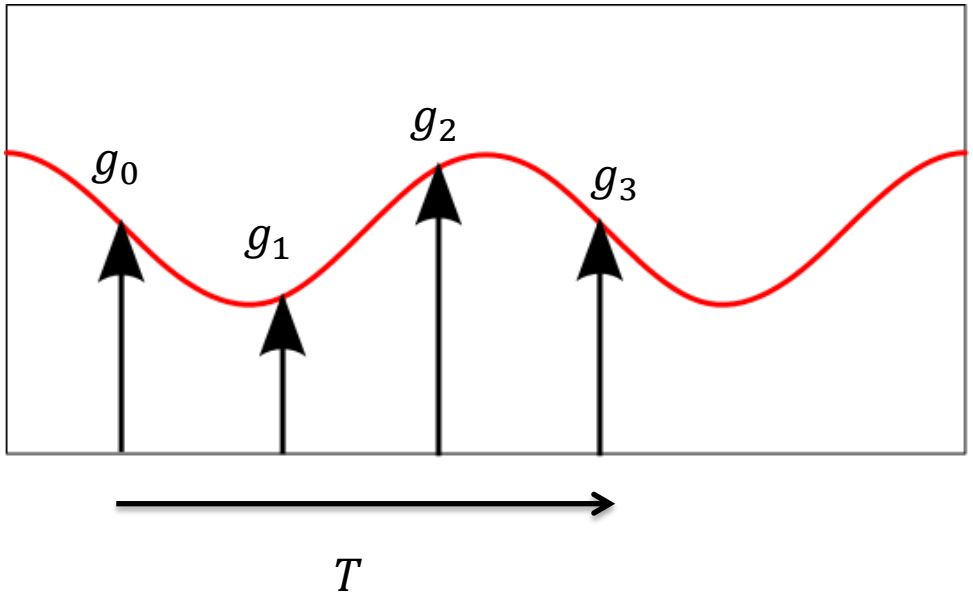
Time-of-Flight principle

- Emitted signal: $f(t) = a\cos(\omega t)$
- Received signal: $g(t) = b\cos(\omega t + \varphi)$
- Distance is proportional to phase: $d = D\frac{\varphi}{2\pi}$
- D is the maximum unambiguous range of the sensor
- For example, $D = \frac{\text{speed of light}}{2\times 20\text{MHz}} \approx 7.5\text{m}$
- Ambiguous for further distances
- Albedo is related to amplitude b
- Confidence in can also be estimated from amplitude

Time-of-Flight measurement

- Frequency ω of $g(t) = b\cos(\omega t + \varphi)$ is known
- Take four equally-spaced samples per period $T = \frac{2\pi}{\omega}$
- $g_k = b\cos\left(\omega\left(\frac{kT}{4}\right) + \varphi\right)$

$$g_0 = b\cos(\varphi)$$
$$g_1 = -b\sin(\varphi)$$
$$g_2 = -b\cos(\varphi)$$
$$g_3 = b\sin(\varphi)$$



$$\varphi = \tan^{-1}\left(\frac{g_3 - g_1}{g_0 - g_2}\right)$$

$$b = \frac{1}{2}\sqrt{(g_3 - g_1)^2 + (g_0 - g_2)^2}$$

Biological analogies

- Bats also estimate distance from (sound) reflections
- But not by simple phase measurements

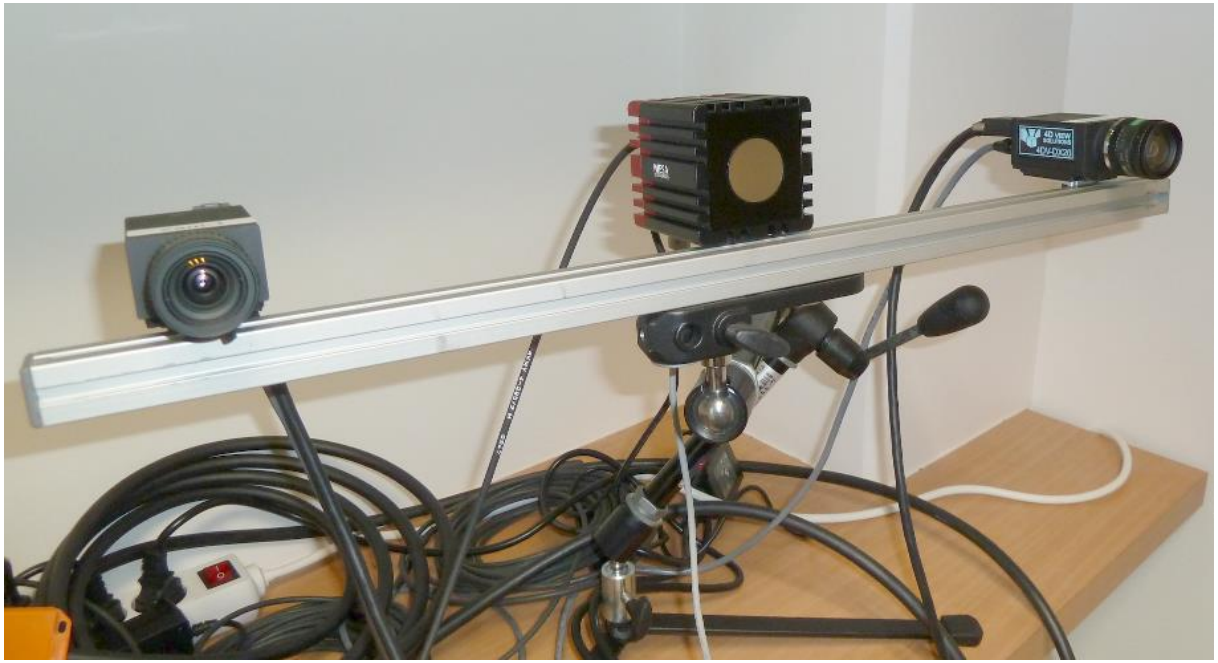
Also dolphins, electric fish, etc

Stereo vs TOF reconstruction

- Need the TOF/stereo transformation for rendering
- TOF 3D contains a lot of local errors
  - Sensor noise
  - Scattering surfaces
- Stereo 3D often has global errors
  - Overall distortion of the scene
  - Caused by lack of camera *calibration*
- The two reconstructions are complementary

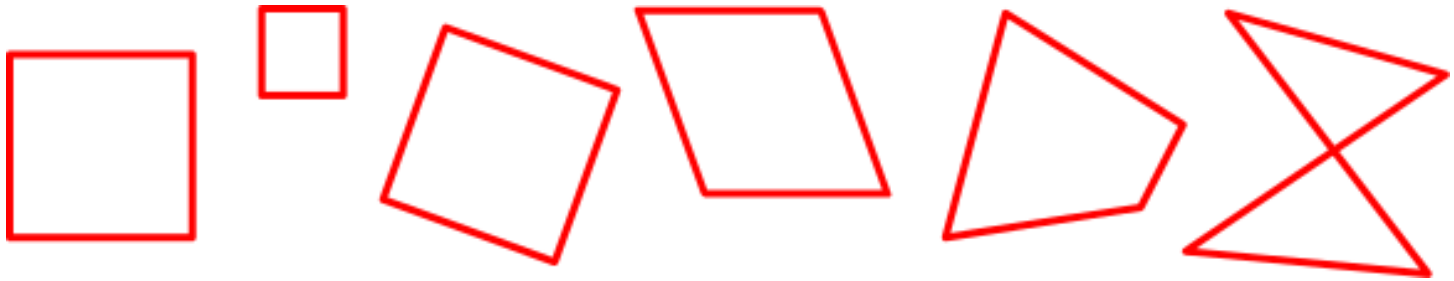
Mixed camera-systems

- Each system provides two 3-D reconstructions
- One TOF camera + two high-resolution RGB cameras
- Several of these TOF+2RGB systems can be combined



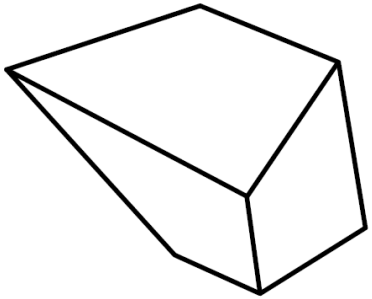
Projective alignment: theory

- TOF/stereo viewpoints and methods are different
- How are the two reconstructions related in 3D?
- Not just rotation, translation and scale
- But *flat* surfaces are flat in *both* reconstructions
- Flatness-preserving transformations are projective
- Examples of projectively equivalent shapes in 2D:

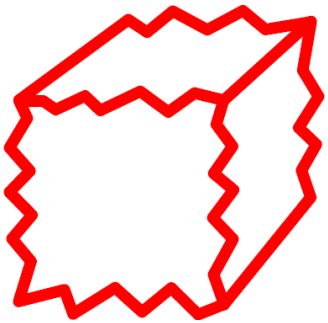


Projective alignment: algorithm

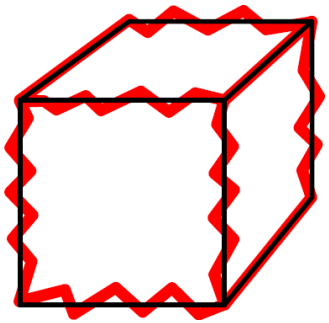
- Align the uncalibrated stereo reconstruction to the TOF data, by 3D projective transformation
- Can be done by a *linear* method (SVD based)
- Now any TOF point can be projected into the images, so the model can be *rendered*



Stereo reconstruction



TOF reconstruction



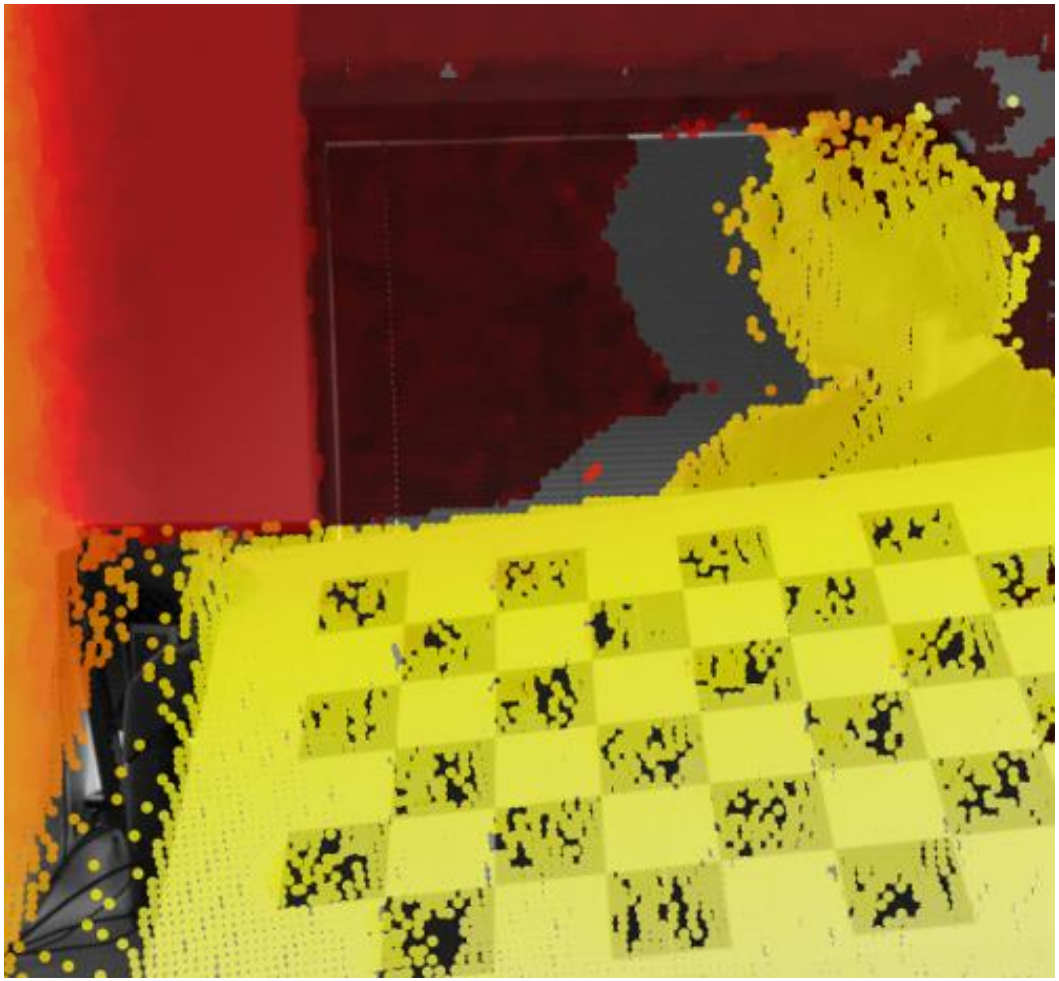
Combined reconstruction

Reprojection results

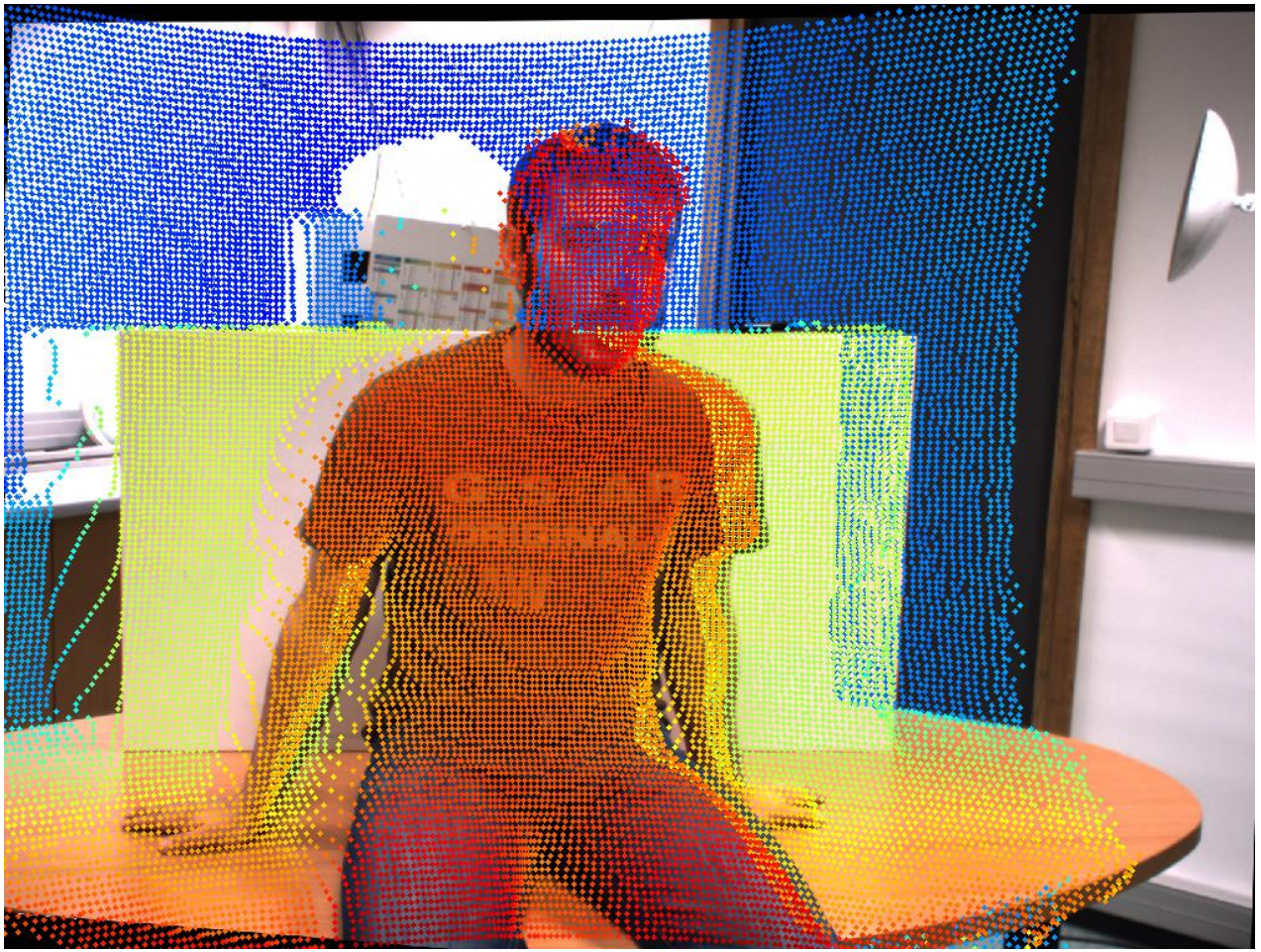
- To associate a colour with each 3-D point:
  - Backproject the TOF pixels to XYZ in the scene
  - Reproject them into RGB views (using estimated cameras)

Left, TOF, and right images, colour-coded by depth

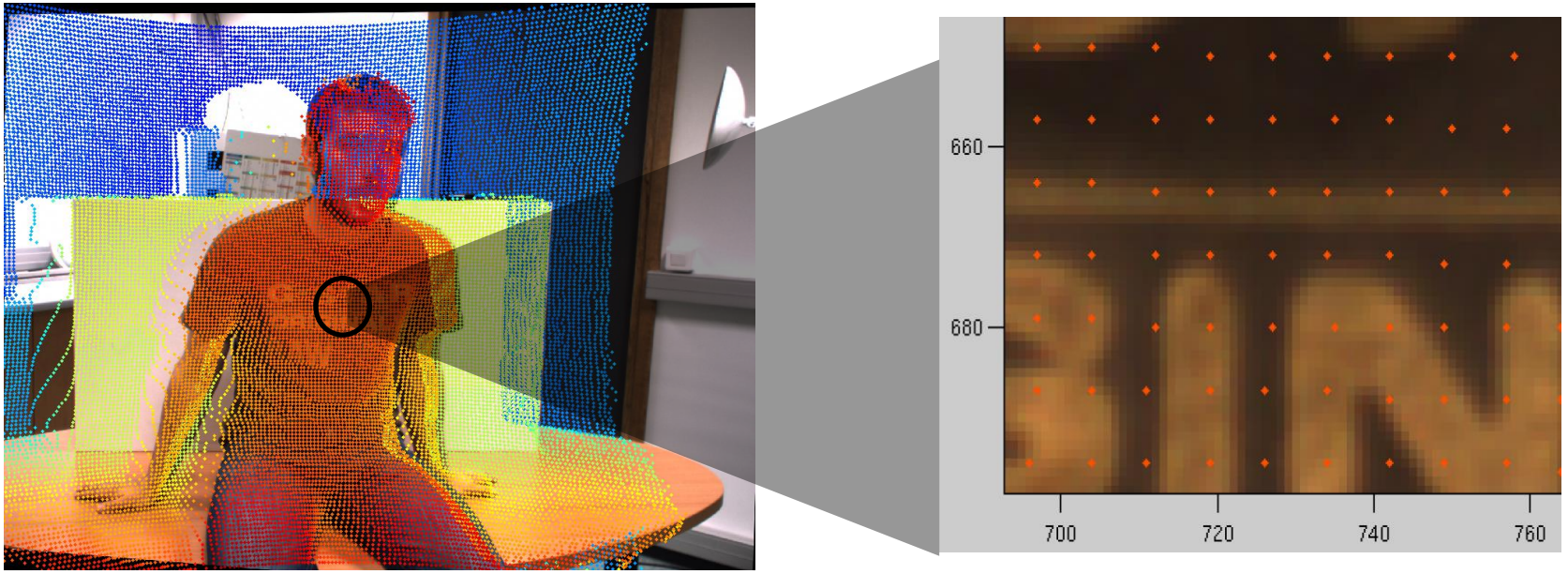
Reprojection results - detail



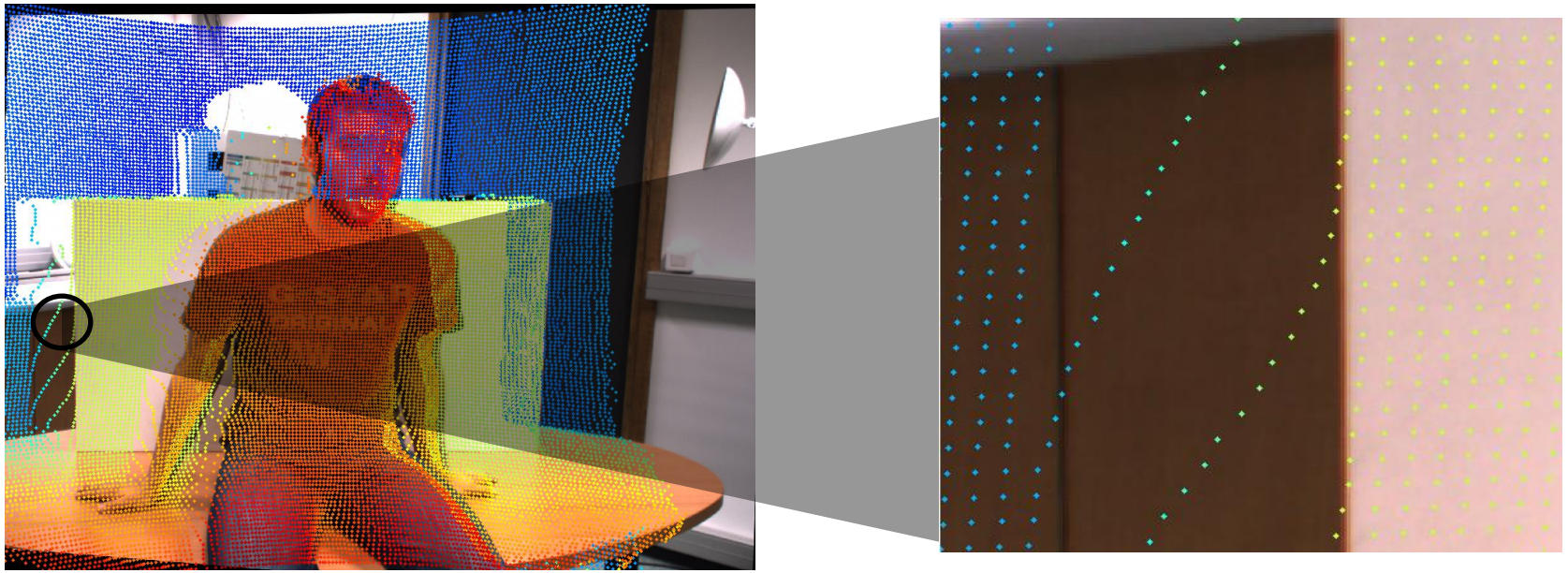
Wide-baseline example



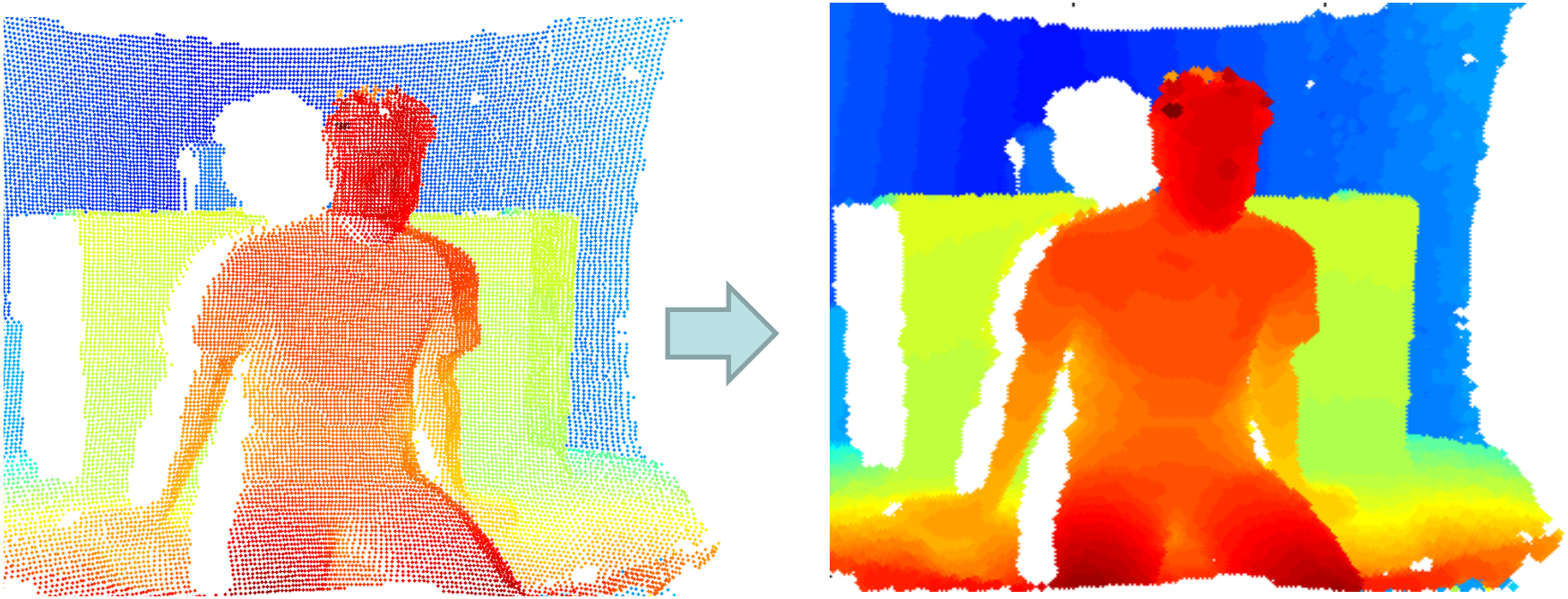
Resolution mismatch



Problems at depth-boundaries



From TOF to dense depth

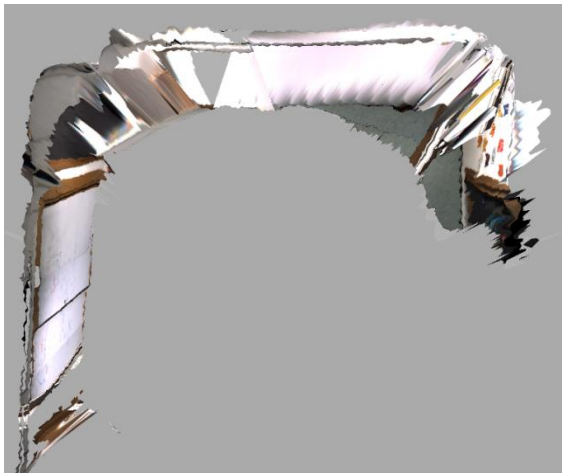


Full four-system configuration

Setup is designed for 360° capture of human figures

Multi-system alignment

- Each TOF+2RGB system has been calibrated
- We now align the four stereo reconstructions
- One system is chosen to be the reference-frame
- We use (4-1) rigid + 4×2 projective transformations



Top view

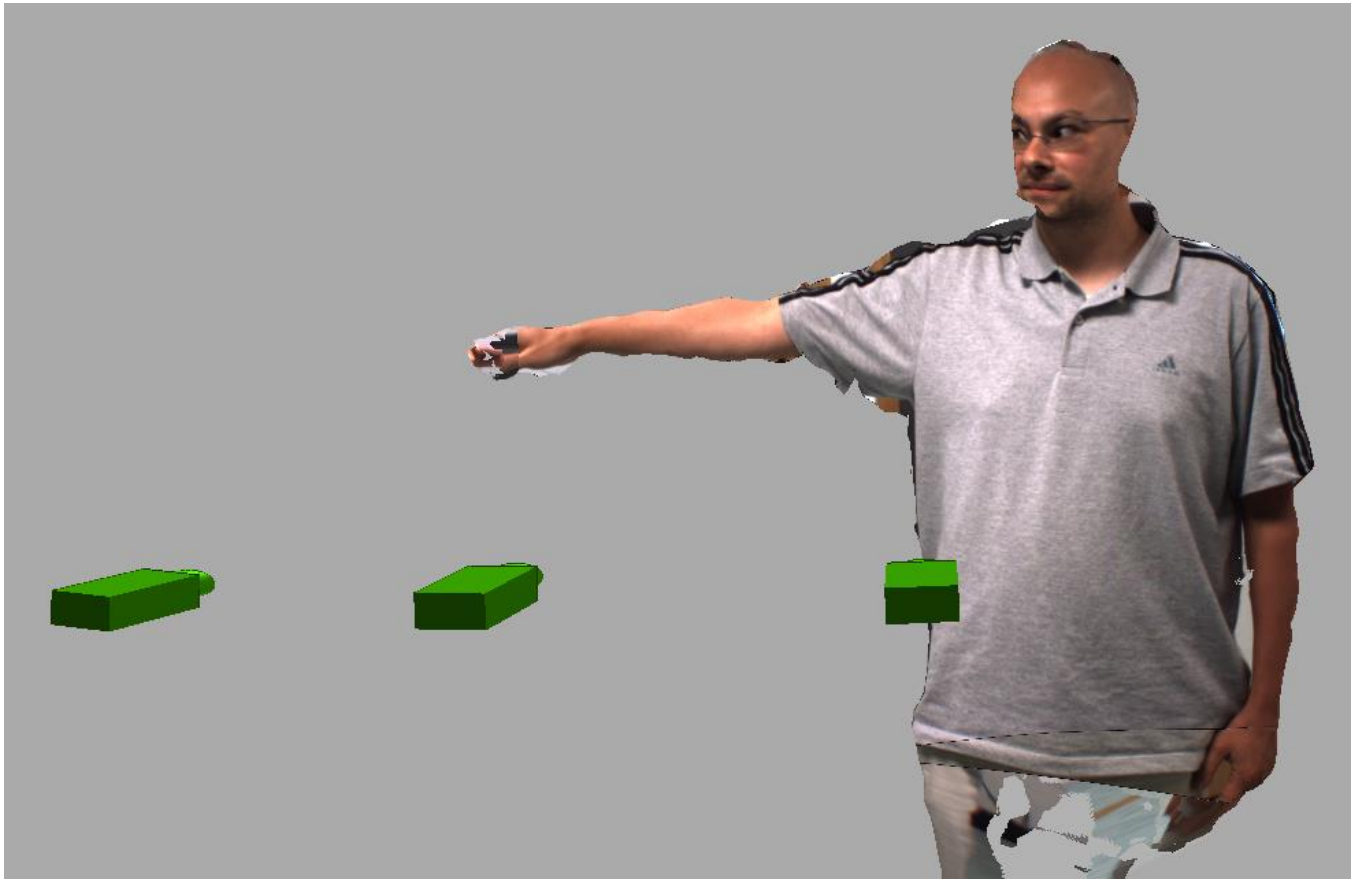
Meshing

- Complete figure + room reconstructions give rise to difficult meshing problems
- Use the TOF data to pre-segment the figure
- Background can then be meshed easily, using a local method
- The figure can be meshed using a global method (e.g. Poisson Reconstruction)
- Also allows one or more figures to be placed in an alternative background
- No completely satisfactory solution yet!

Rendering

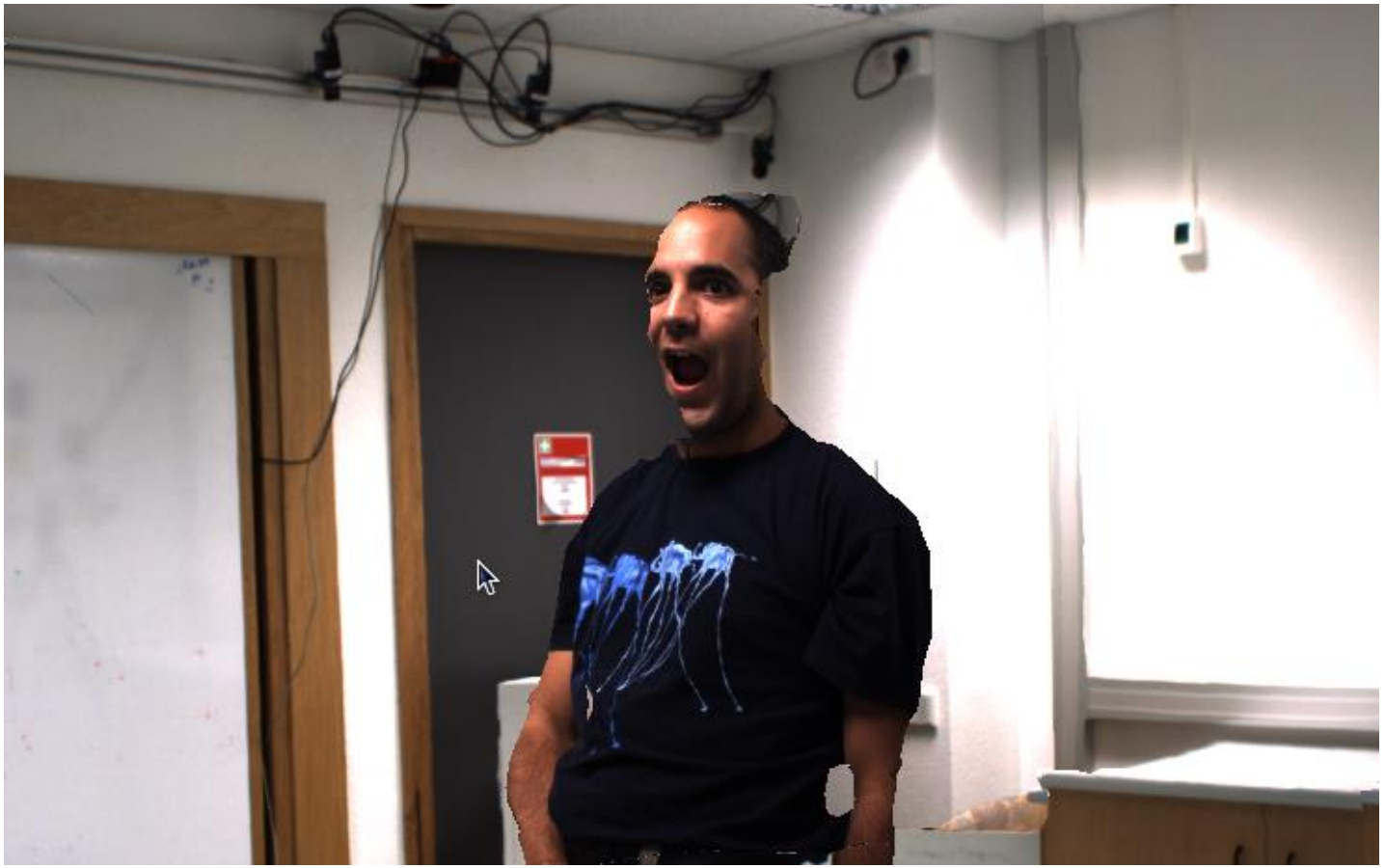
- Mesh representation is rendered using standard graphics hardware (OpenGL shaders)
- An additional advantage of the alignment method is that multiple textures are available
- Blended, or switched according to relationship between the surface and viewpoint
- Models are rendered in real-time, using live TOF+RGB data.

Segmented figure



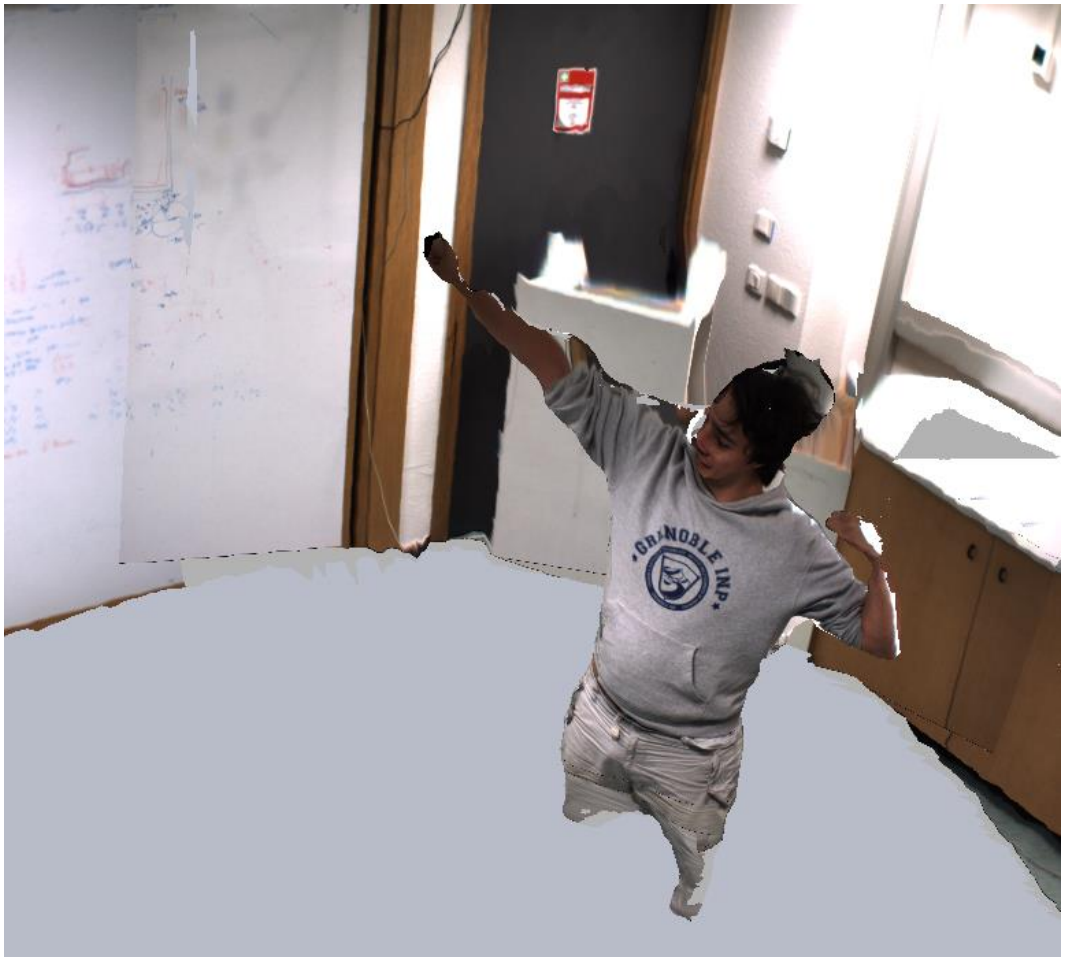
The cuboids represent one of the TOF+2RGB systems

Rendered figure & background



Note sharp boundary between figure and background

Rendered figure & background



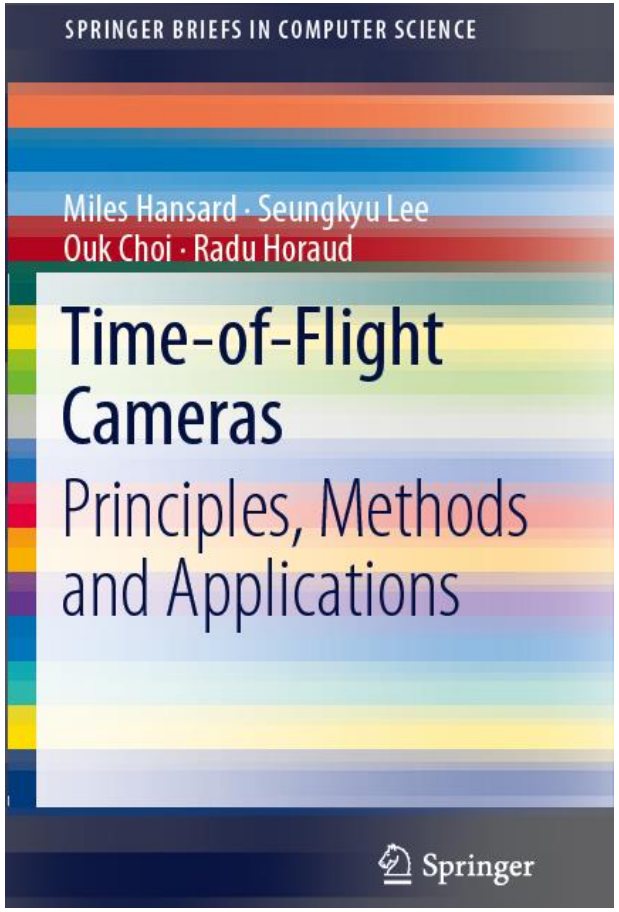
Top view of a three-system reconstruction

Reprojected figure-mesh

3D mesh, reprojected into one of the texture-images

Figure reconstructions

Springer monograph (2012)

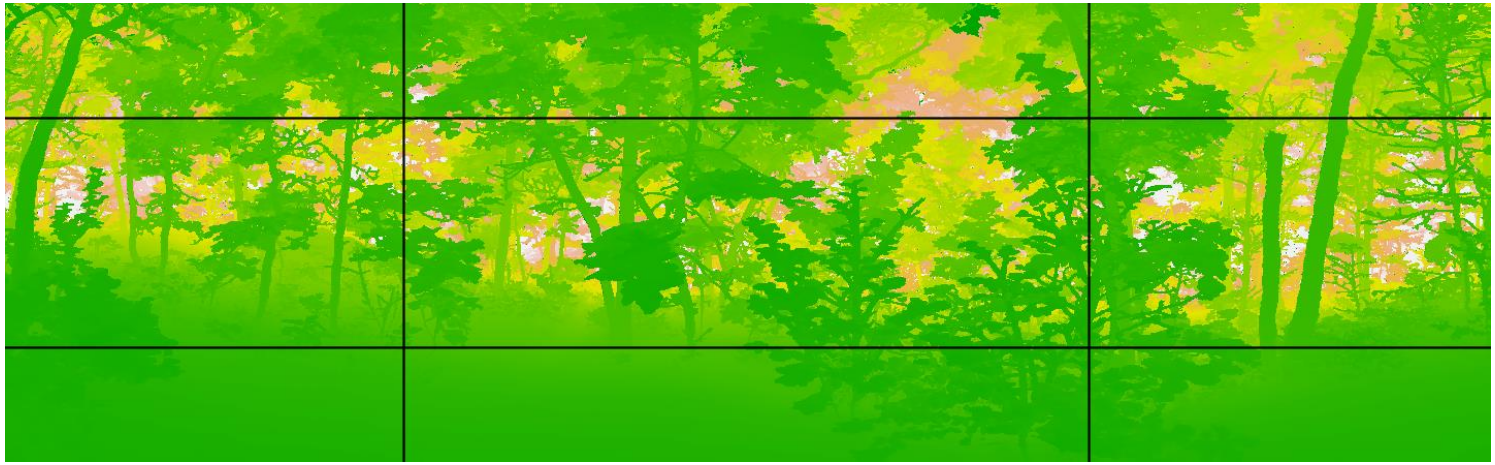


Collaborators

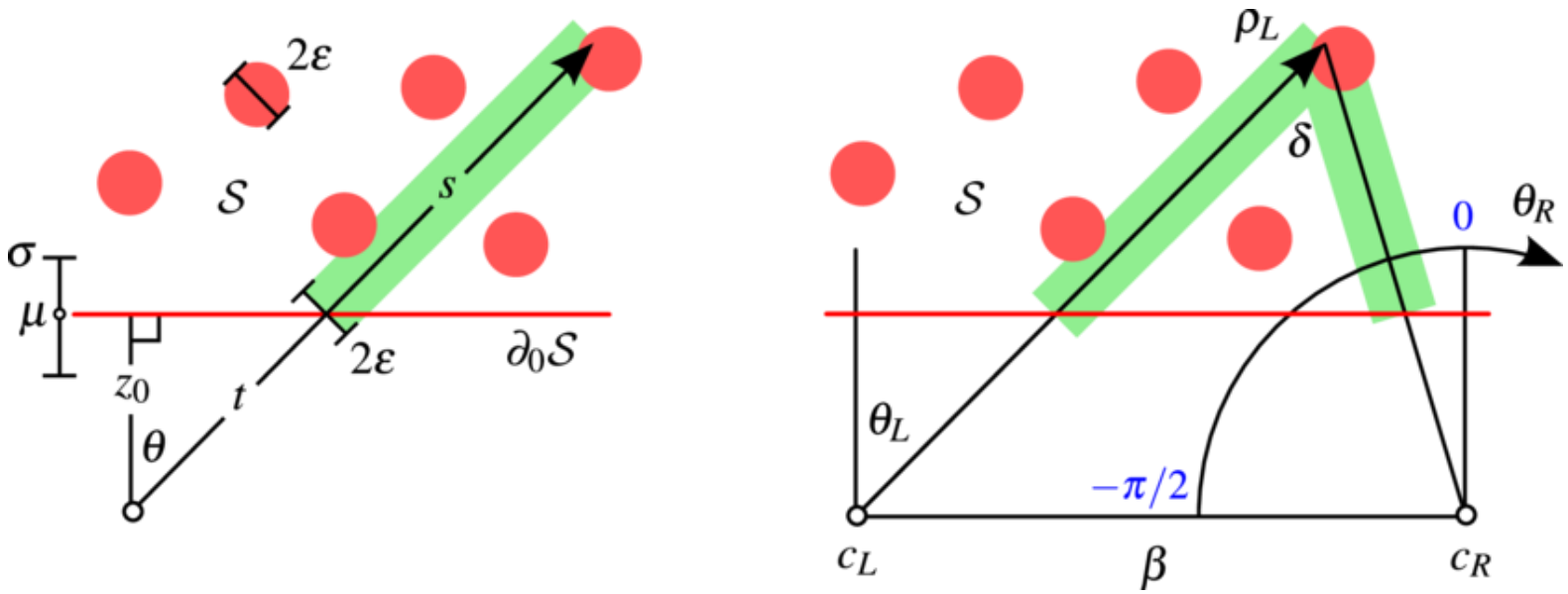
- Radu Horaud, Georgios Evangelidis, Michel Amat
  - INRIA Grenoble, France
- Seungkyu Lee, Ouk Choi
  - Samsung Advanced Institute of Technology, South Korea

Random scenes

- Highly cluttered environments, in which the depth-structure is not dominated by any particular object
- E.g. forests (important for evolution!)
- Very wide-angle laser range-scan:



Geometric model



- Left: Green rectangle must be empty for visibility
- Right: Both must be empty for binocular visibility
- Red line is the scene-boundary (empty in front)

Scene and observer models

- If scene has a Poisson distribution of intensity λ, then distance to visible object has exponential distribution F:

$$\text{prob}(s|\lambda) = F(s, 2\varepsilon\lambda)$$

- This is not realistic in typical imaging conditions
- Peak of distribution along any ray would be at zero (the optical centre)
- Impose a scene-boundary, at random distance from the observer, according to Gaussian distribution G:

$$\text{prob}(t|\theta, \mu, \sigma) = G\left(t, \frac{\mu}{\cos\theta}, \frac{\sigma}{\sin\theta}\right)$$

Binocular joint-distribution

- Total distance to first object along a ray is the scene-penetration *plus* the distance to the scene-boundary
- Probability of a sum $\rho = s + t$ is the *convolution* of the densities $F(s)$ and $G(t)$
- This is a re-parameterized ex-Gaussian distribution H:

$$\text{prob}(\rho|\theta) = H\left(\rho, 2\varepsilon\lambda, \frac{\mu}{\cos\theta}, \frac{\sigma}{\cos\theta}\right)$$

- Tend to see fewer distant objects, in clutter
- A point is binocularly visible if *both* left and right rays are unobstructed:

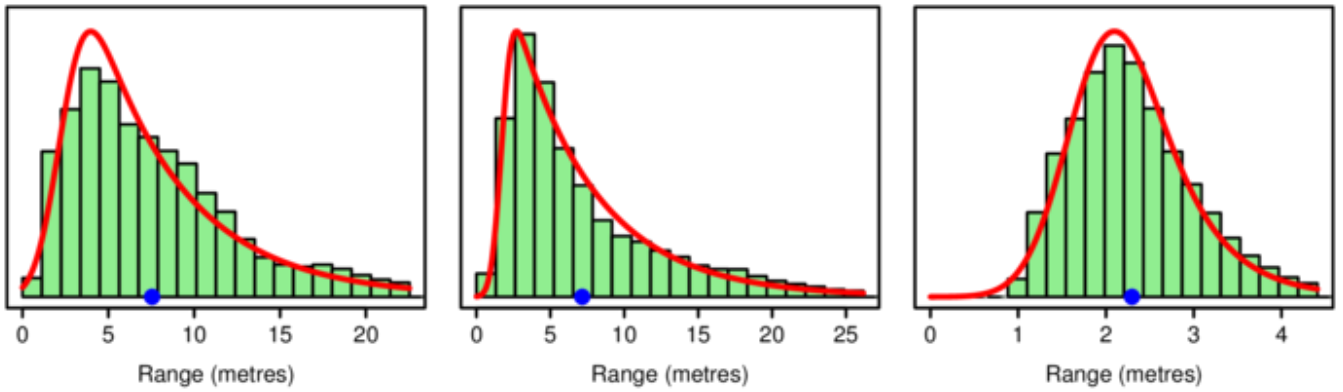
$$\text{prob}(\rho_L, \rho_R) = \text{prob}(\rho_L|\theta_L) \times \text{prob}(\rho_R|\theta_R)$$

Fits to forest data

- The parameters to be estimated are $2\varepsilon\lambda$, μ and σ

$$\text{prob}(\rho|\theta) = H\left(\rho, 2\varepsilon\lambda, \frac{\mu}{\cos\theta}, \frac{\sigma}{\cos\theta}\right)$$

- Each fit defines a one-parameter family, ranging from coarse/dense to fine/sparse
- Maximum Likelihood fits, by numerical minimization:



Monocular conditional-distribution

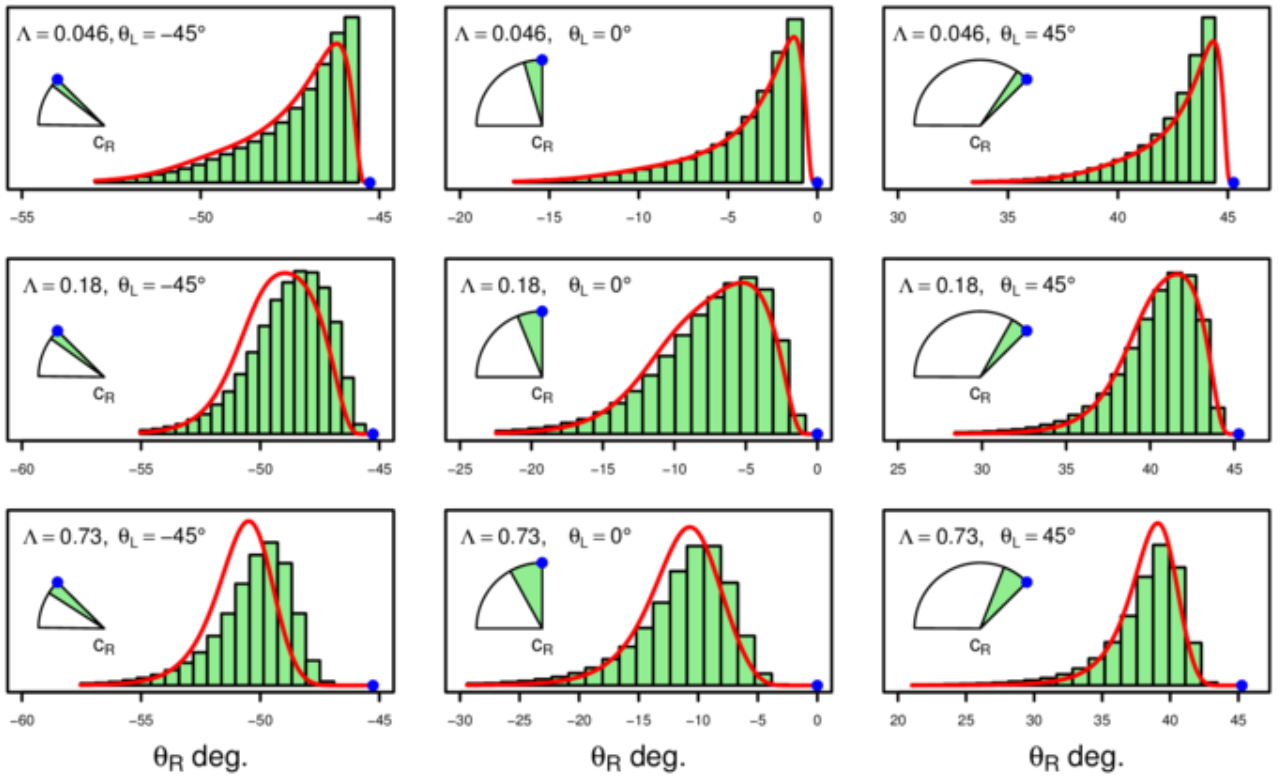
- Joint-distribution determines several other distributions
- But the joint-distribution is not *observable*; it is parameterized by *scene*-distances
- More useful to ask: given an image point in one view, where is the corresponding point in the other view?
- This is the *conditional* distribution along an *epipolar line*:

$$\text{prob}(\theta_R|\theta_L) = \text{prob}(\rho_L, \rho_R) \times J_R(\theta_R)/S_R(\theta_L)$$

- Jacobian $J_R(\theta_R)$ and normalizing constant $S_R(\theta_L)$ ensure that $\text{prob}(\theta_R|\theta_L)$ is a proper probability density
- Tend to see more of a scene, 'per pixel', in the distance

Prediction of re-projected forest data

- The image densities can be used as Bayesian priors for image-matching in cluttered scenes
- These are *predictions*, not fits, given the estimated density:



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