Photogrammetry position calibration of water Cherenkov detectors

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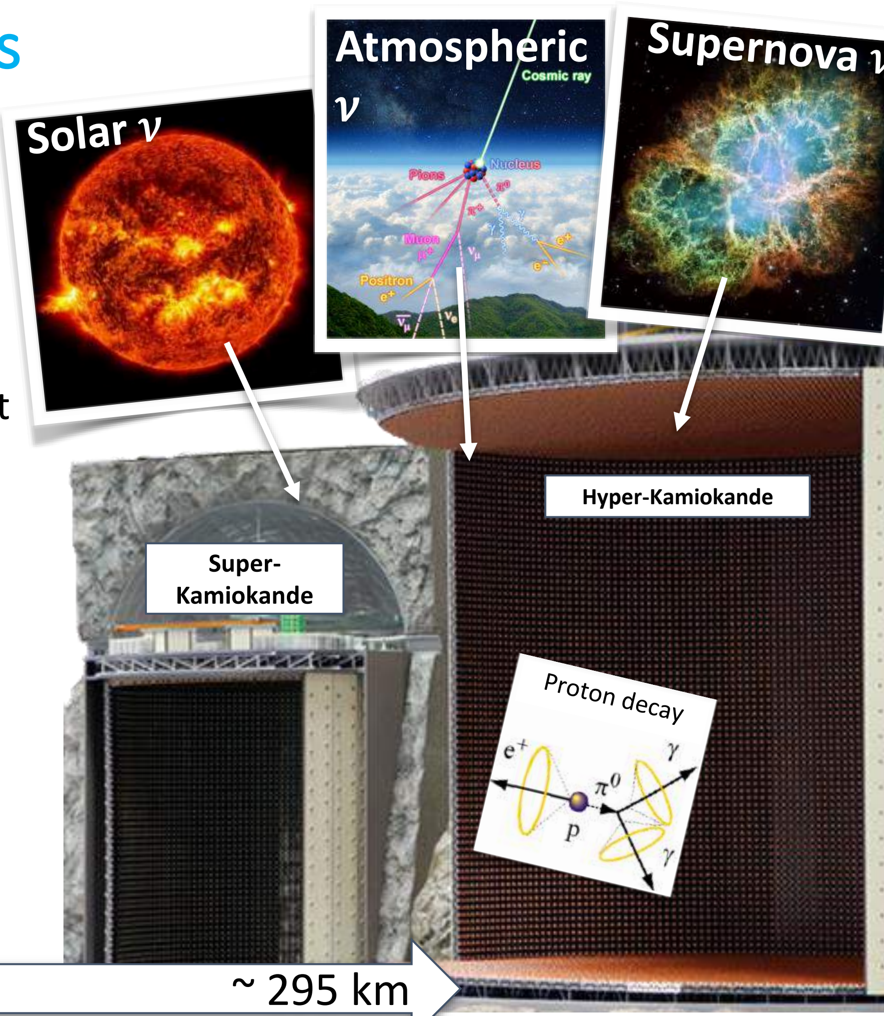
The Super-K & Hyper-K Experiments

Current generation **Super-K** and next generation **Hyper-K** are world-leading neutrino experiments

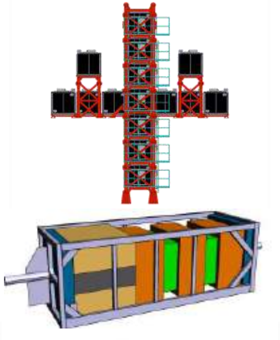
Broad & ambitious physics programmes covering many neutrino sources and proton decay measurements

Water Cherenkov detector technology provides huge target mass with excellent particle ID and reconstruction capabilities

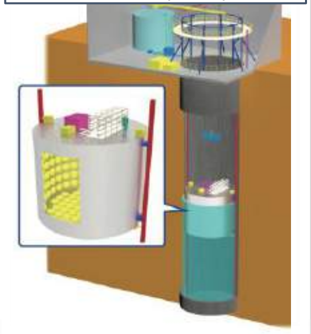


Water Cherenkov Test Experiment (WCTE) at CERN

Near detectors



Intermediate Water Cherenkov Detector (IWCD)

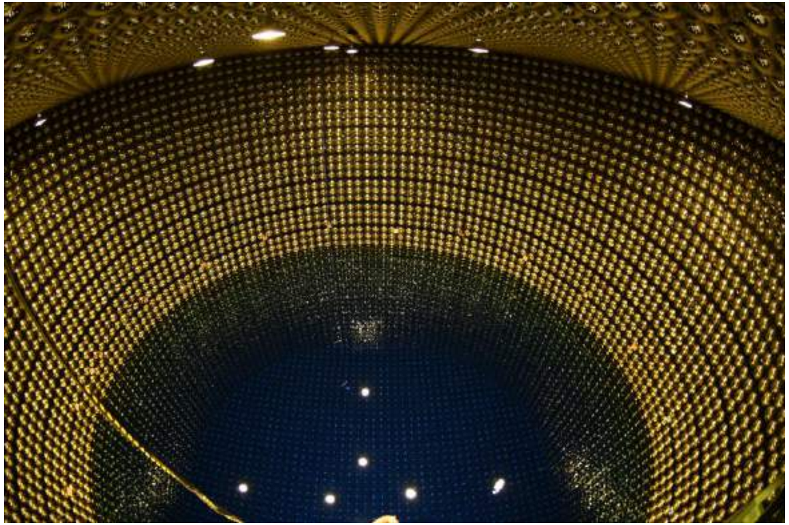


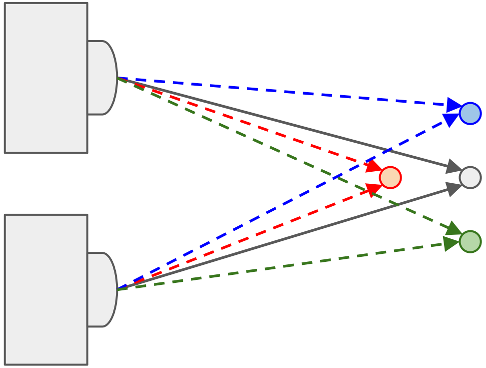
280 m → ~ 1 km → ~ 295 km

Also see Talks by P. de Perio (T2K/HK), V. Gousey-Leblanc(PTF), N. Prouse (ML), R. Akutsu (neutrons), M.Yu (CCπ0),), and L. Koerich (mPMT)
Posters: M. Sekatchev (more photogrammetry), B. Ferrazi (ARICH reflectors), S. Wingfelder (HK PMT)

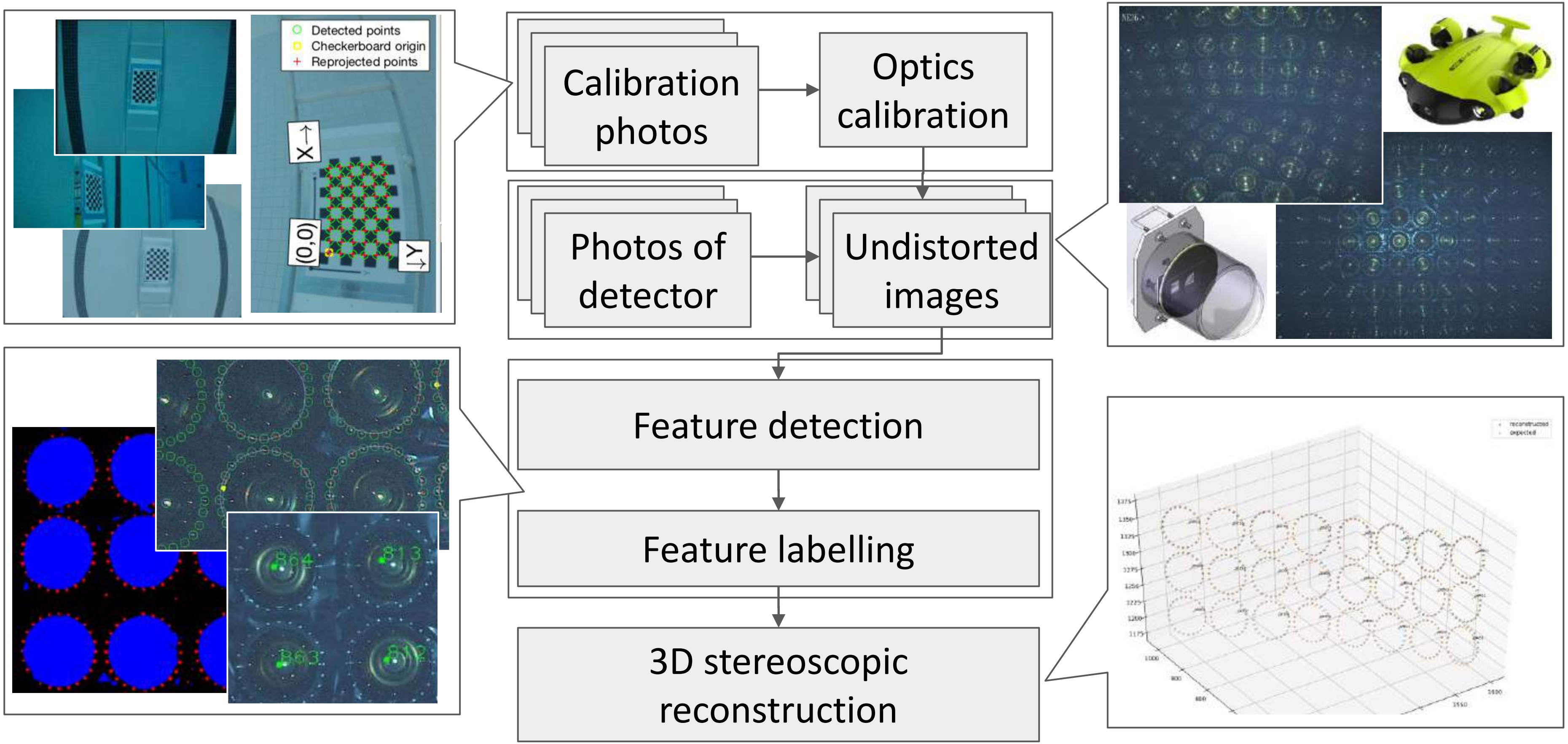
Photogrammetry motivation

- As measurements become more precise, accurate calibration of all detector aspects becomes more critical
- Over time and during water filling, buoyancy forces on large vacuum-filled PMTs could cause small systematic shifts in their positions
- Confirmation of the PMT positions could reduce systematic effects on particle reconstruction
  - e.g. require < 1% error on fiducial volume
- In-situ measurement of PMT positions can directly quantify this effect independently of other effects
- **Photogrammetry** uses stereoscopic reconstruction: photographs from multiple locations to measure the 3D geometry

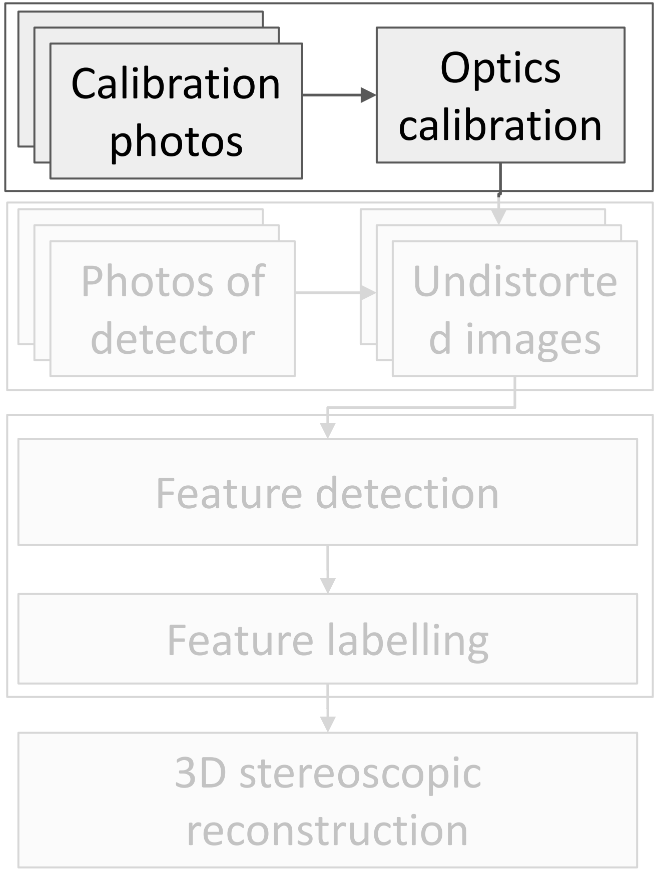




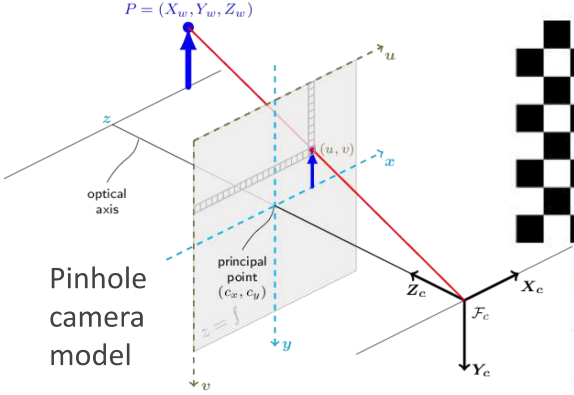
Photogrammetry procedure overview



Camera calibration



- Camera model transforms 3D locations to 2D image pixels



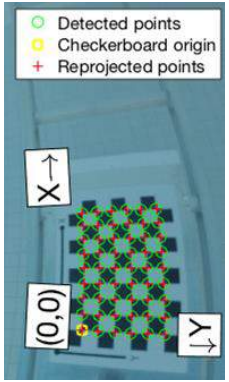
Pinhole camera model

$$\begin{bmatrix}u\\ v\end{bmatrix}=\begin{bmatrix}f_x x''+c_x\\ f_y y''+c_y\end{bmatrix}\qquad \begin{bmatrix}x'\\ y'\end{bmatrix}=\begin{bmatrix}X_c/Z_c\\ Y_c/Z_c\end{bmatrix}$$

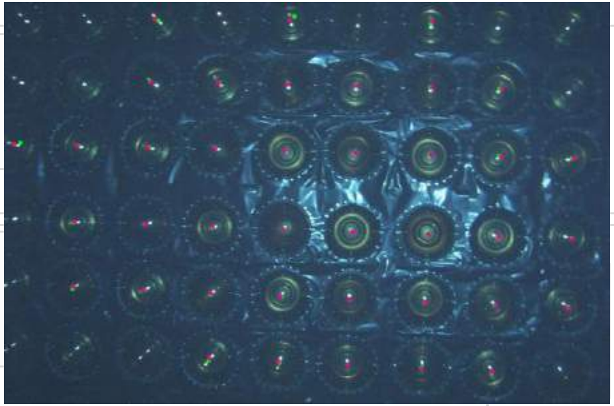
$$\begin{bmatrix}x''\\ y''\end{bmatrix}=\begin{bmatrix}x'\frac{1+k_1r^2+k_2r^4+k_3r^6}{1+k_4r^2+k_5r^4+k_6r^6}+2p_1x'y'+p_2(r^2+2x'^2)+s_1r^2+s_2r^4\\ y'\frac{1+k_1r^2+k_2r^4+k_3r^6}{1+k_4r^2+k_5r^4+k_6r^6}+p_1(r^2+2y'^2)+2p_2x'y'+s_3r^2+s_4r^4\end{bmatrix}$$

Lens distortion model

- Underwater photos taken in pool with checkerboard calibration pattern
- Camera model params determined using MATLAB camera calibration toolbox



Feature Identification

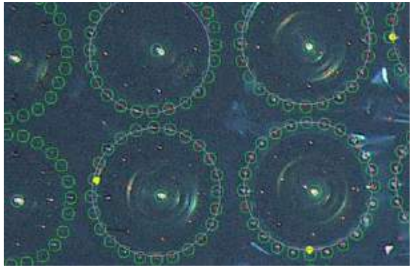


Feature detection

Feature labelling

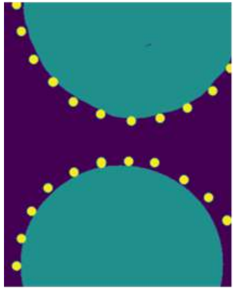
3D stereoscopic reconstruction

- Identifying and matching PMTs in repeating pattern is very challenging
- Image processing methods used for identifying the features to be reconstructed: Bolts and PMT centres
  - Traditional blob detection and Hough transforms
    - Using OpenCV software
  - Machine-learning convolutional neural networks
    - UNet with Image Segmentation Keras package
- Current precision of ~ 2 - 4 pixels
  - Hope to improve on this with further development

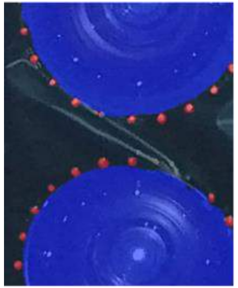


Blob detection & Hough transform ellipse finding

Original image



Segmented by eye for training



Segmented by CNN

(That's my part with Tapendra B C)

What we know to do the feature labelling

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{bmatrix}$$

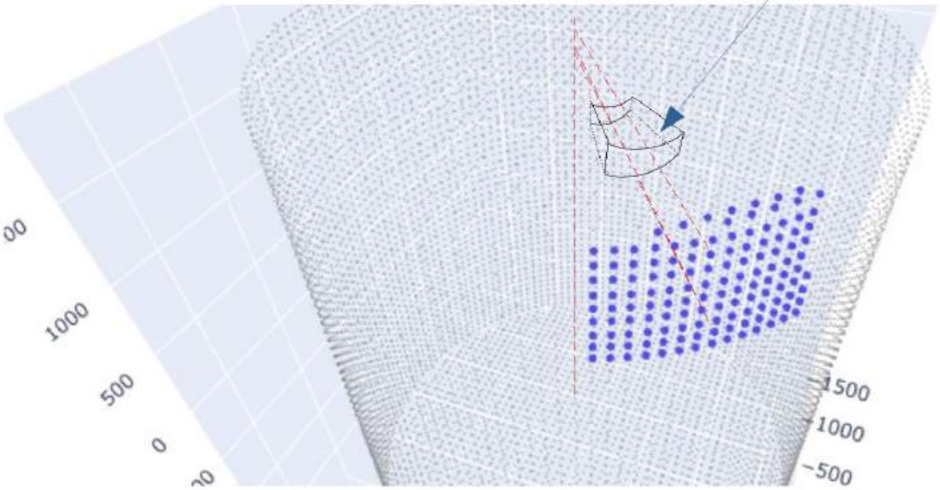
Unknown

Camera Transformation

T: R^3 -> R^2

Domain: Points in (R^3) in view of camera.
Range: points in (R^2) image plane.

Bound for camera location.



Fitting for the camera position

Minimize the square of minimum distance between hough-ellipse and Reprojected points.

$$\mathbf{X}_{\mathbf{Camera}} = R_{CW} * \mathbf{X}_{\mathbf{world}} + \mathbf{t}$$

$\mathbf{X}_{\mathbf{Camera}}$ = (0,0,0) for camera position in camera coordinate.
$\mathbf{X}_{\mathbf{world}}$ = Position of camera in world coordinate be P (if we know)

$$\mathbf{0} = R_{CW} * \mathbf{P} + \mathbf{t}$$

$$\mathbf{t} = -R_{CW} * \mathbf{P}$$

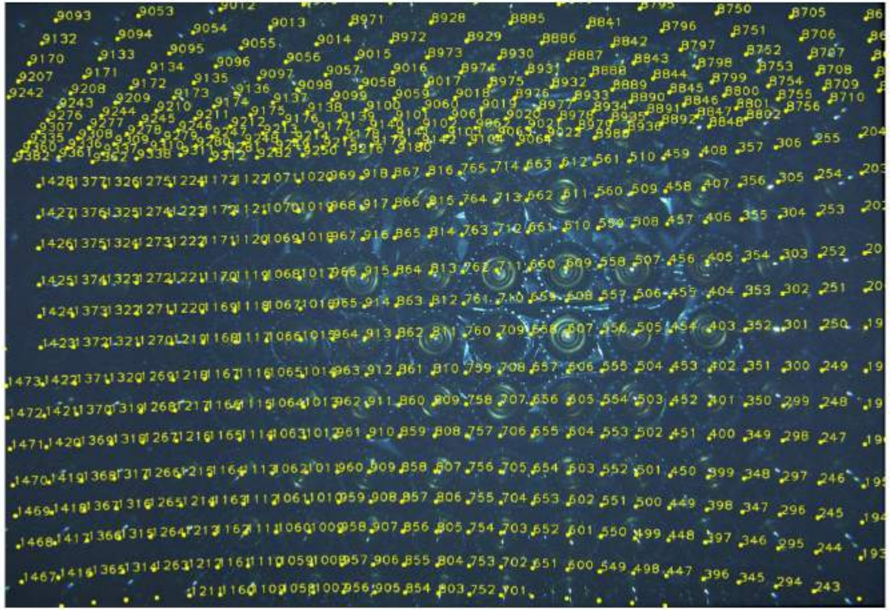


Fig: Re-projected image for particular position.

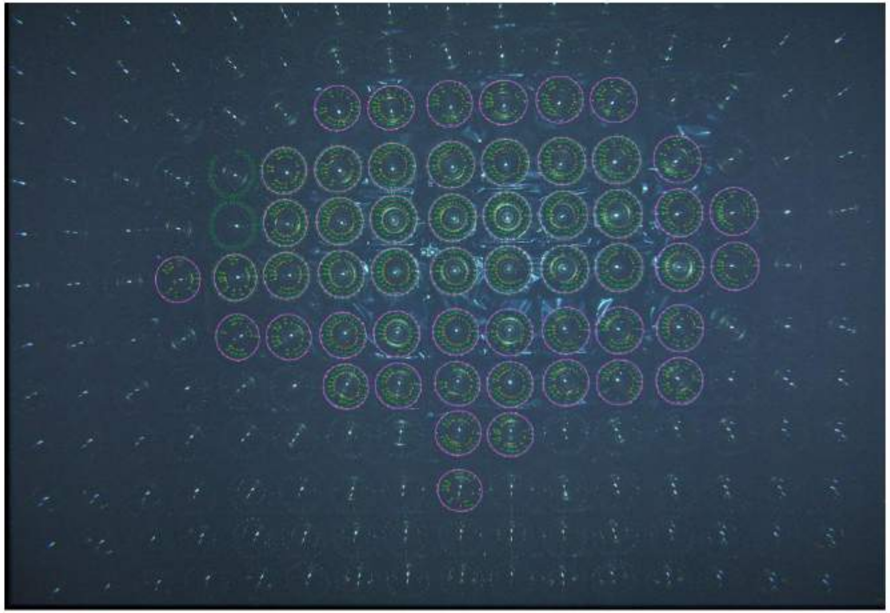
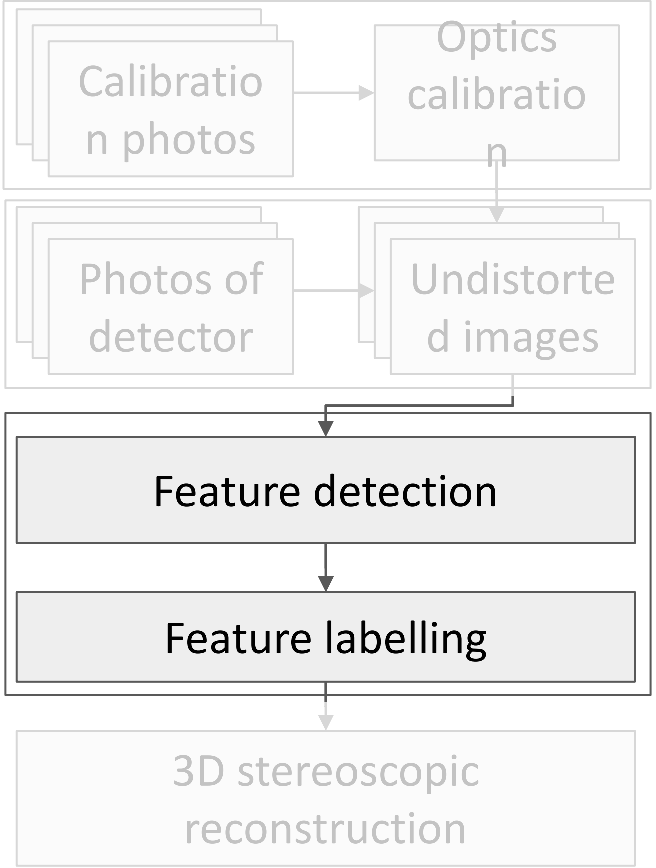
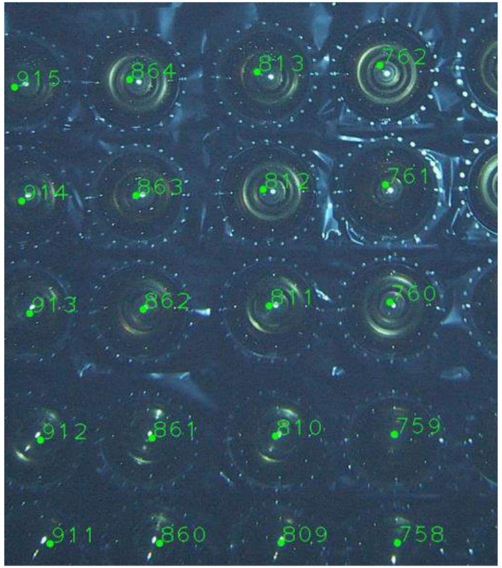


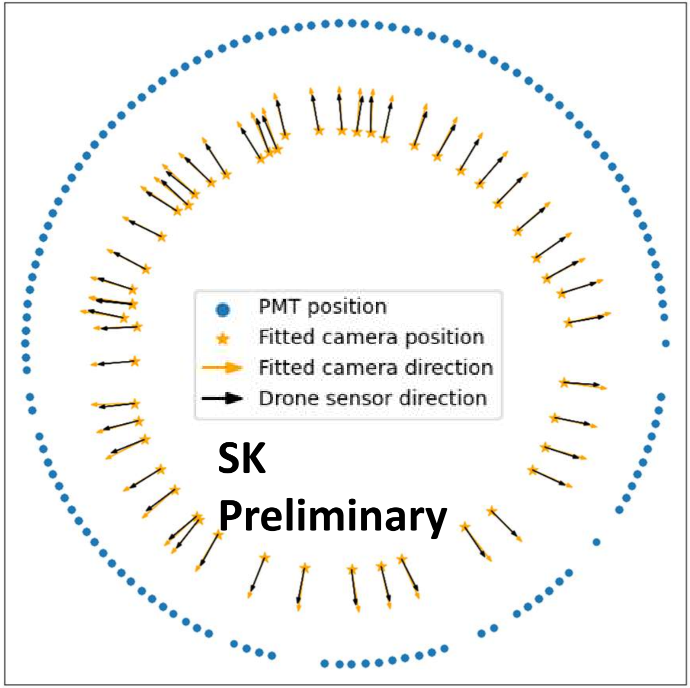
Fig: Detected ellipses from hough-ellipse detection.

Feature Labelling



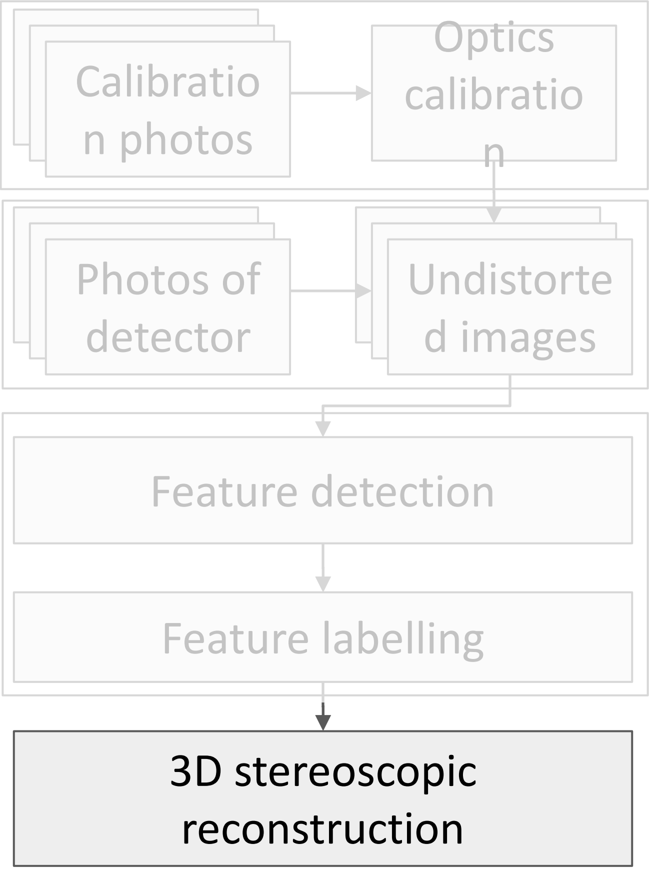
- Identifying and matching PMTs in repeating pattern is very challenging
- Camera position or submarine sensors used to match features between images





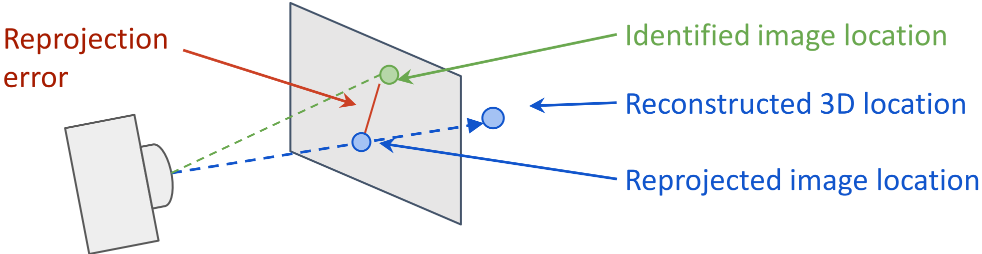
Note: gaps due to lack of overlapping photographs at some locations

Stereoscopic reconstruction



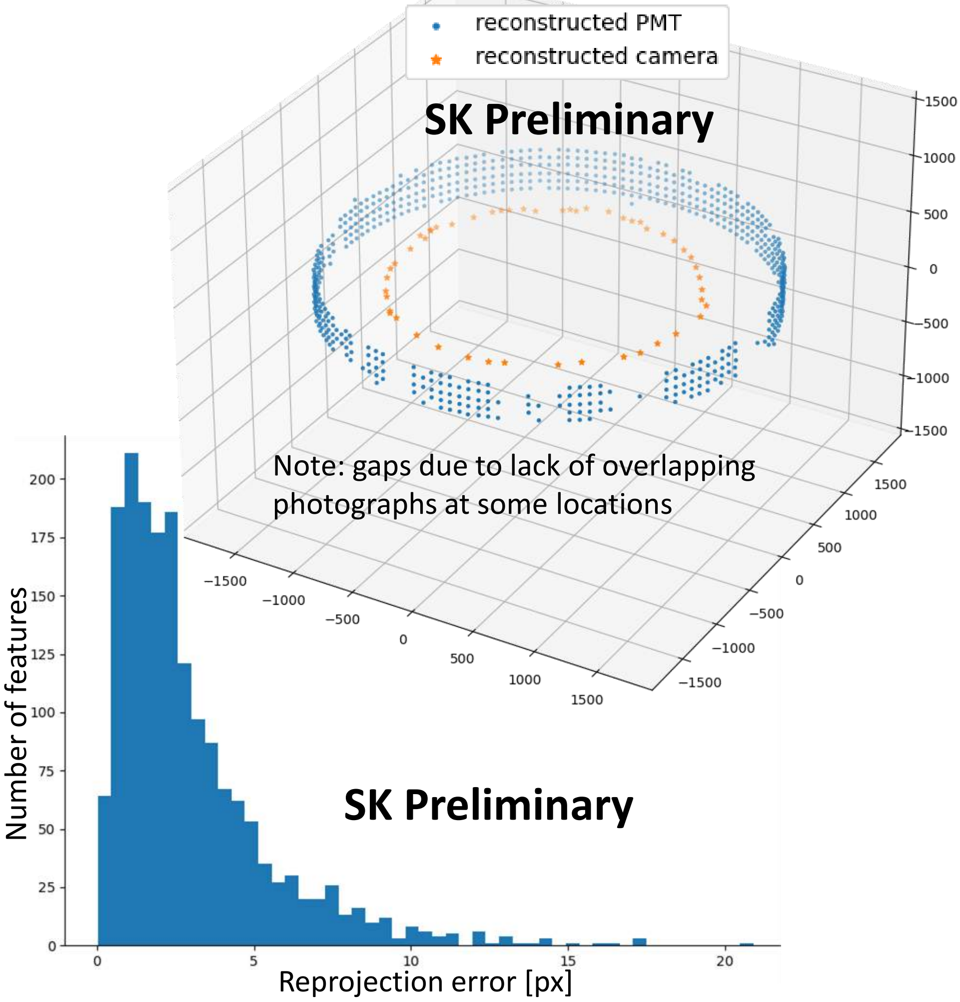
Use OpenCV to perform photogrammetric reconstruction on of identified feature locations

1. Determine camera poses from assumed ‘expected’ 3D feature positions
   - Camera poses: relative position and orientation in 3D space
2. Fit 3D positions of features ‘bundle adjustment’
   - Vary camera poses and 3D feature positions simultaneously
   - Minimise reprojection errors



Results at Super-K

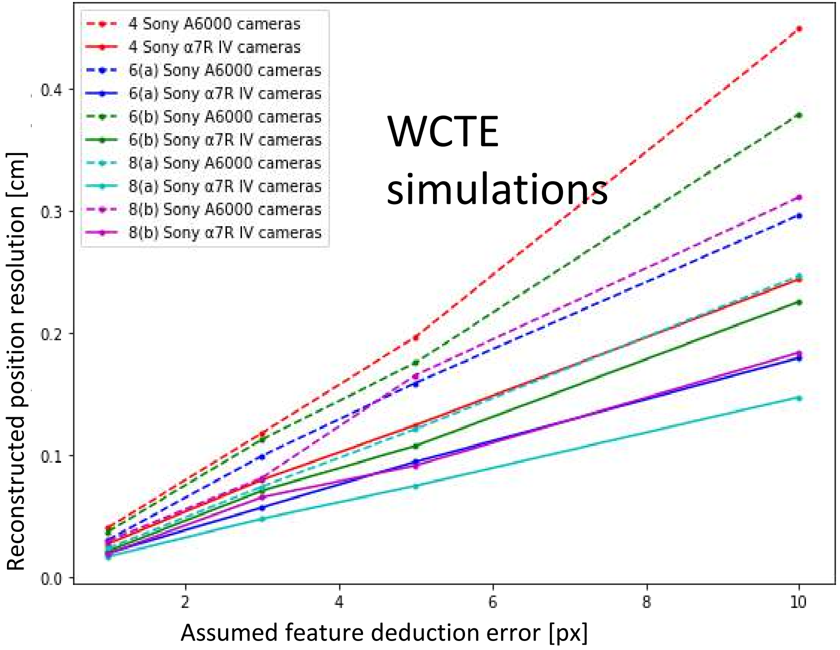
- 3D reconstruction achieved from one ring of images around Super-K
- Analysis of results is currently underway
- Reprojection errors provide measure of fit quality
  - Mean error: 3 pixels
  - 1px error ~ 1 cm position error
- Full tank reconstruction & analysis planned for better understanding Super-K geometry

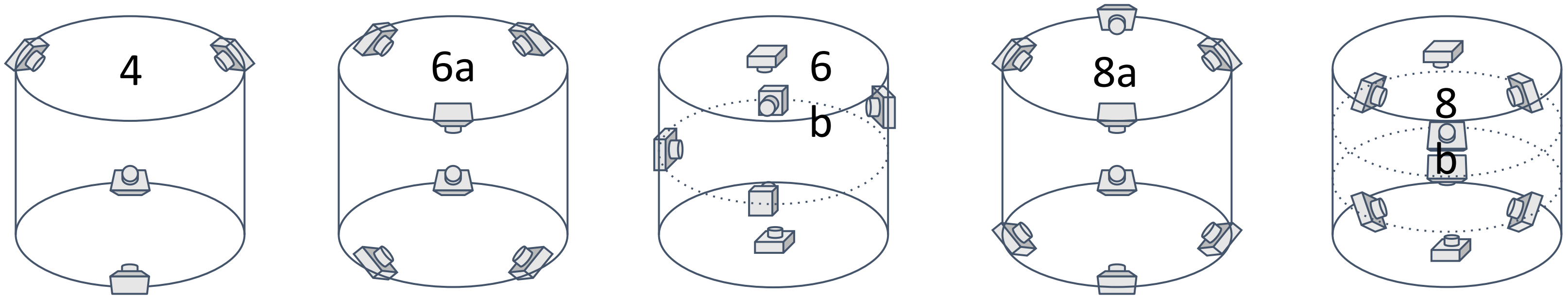


Simulations for future detectors

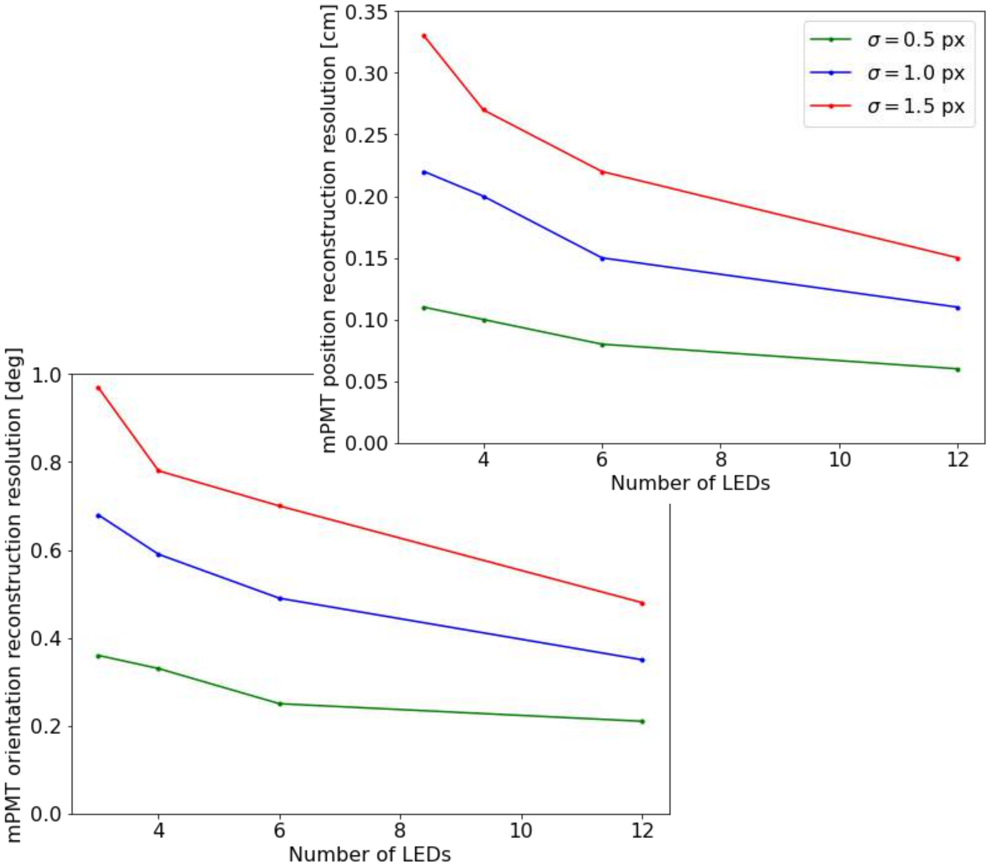
Simulation framework to test photogrammetry configurations

- Simulate images for different detector geometries & camera configurations
- Apply smearing for feature identification error
- Calculate expected 3D reconstruction precision
- Optimise camera configuration for each experiment





IWCD photogrammetry simulations



Increased # of LEDs give small improvement above ~6 LEDs / mPMT

- Resolution scales as $1/\sqrt{N_{LEDs}}$

Might be better to focus on optimising pixel error

- Resolution is almost proportional to pixel error
- Pixel error comes from:
  - Camera resolution
  - Camera calibration accuracy
  - Feature locating accuracy

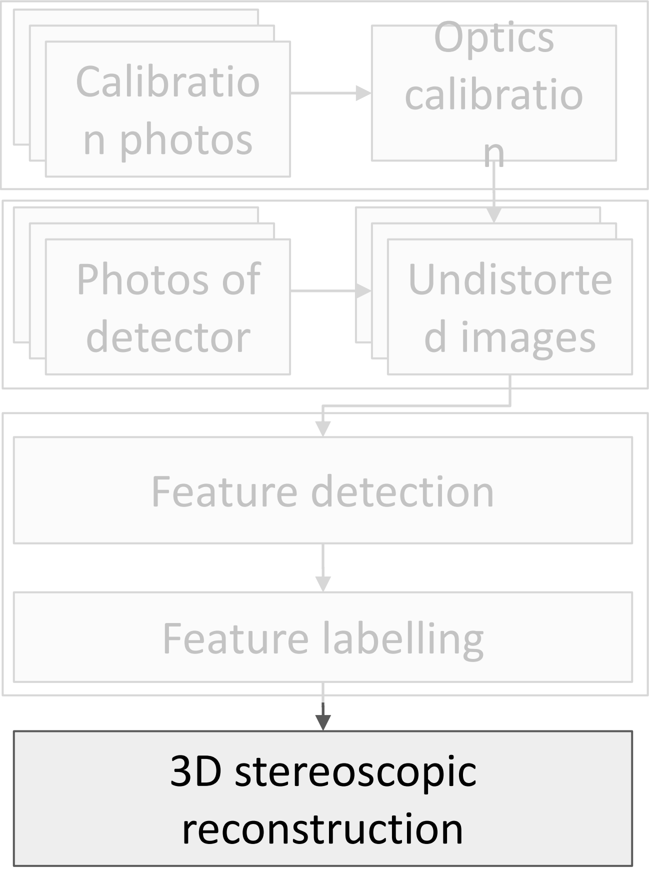
Summary

- As measurements in Water Cherenkov detectors become more precise, accurate calibration of all detector aspects becomes more critical
- Photogrammetry can provide precise in-situ measurement of detector geometry
- With Super-K we have demonstrated the full photogrammetry chain
  - Calibration of cameras, and data taking in the detector
  - Identification and labelling of features to reconstruct in images
  - Stereoscopic reconstruction of 3D geometry
  - Analysis work is ongoing with plan to extend to full detector
- Simulations and R&D for future detectors to optimise hardware configurations and understand physics impact

Thank you for your attention

Appendix

Stereoscopic reconstruction



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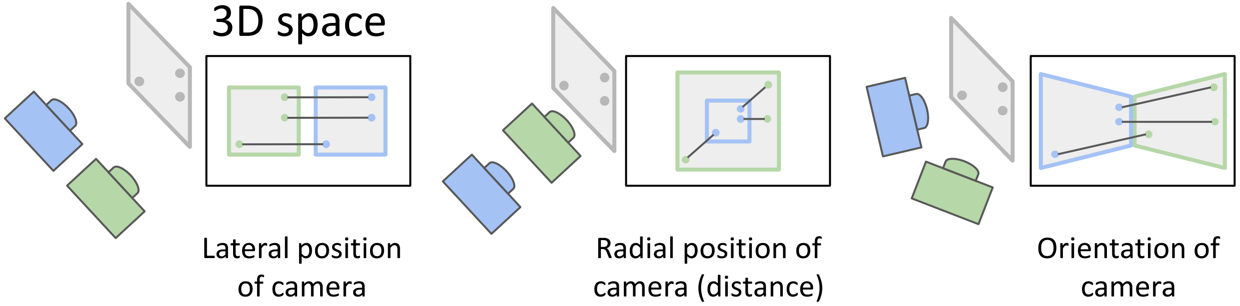
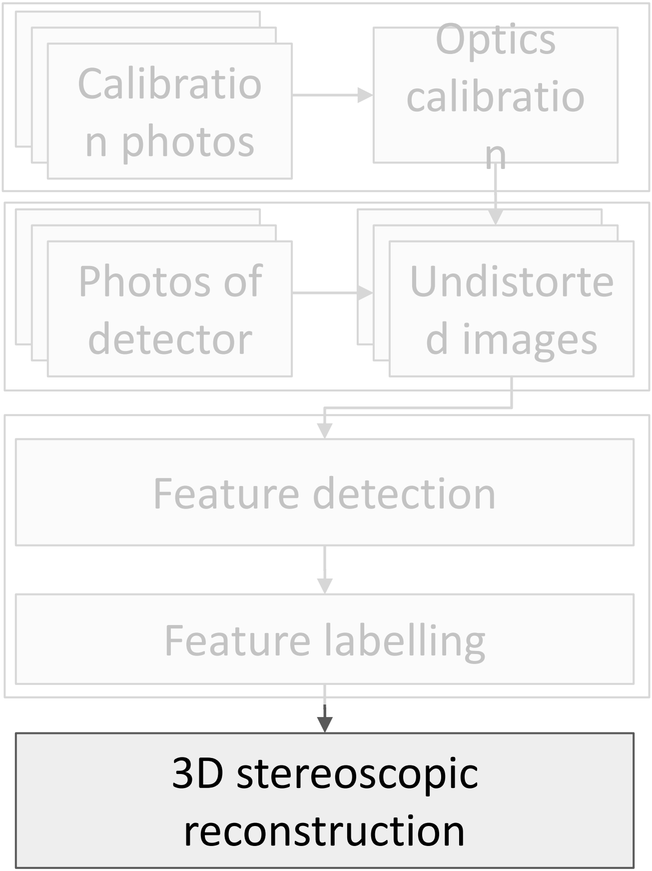


Stereoscopic reconstruction



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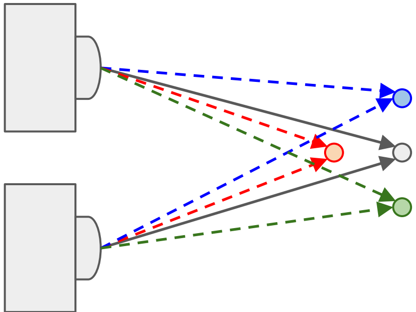

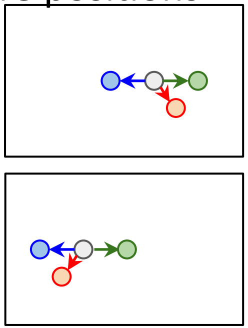

Simulations for future detectors

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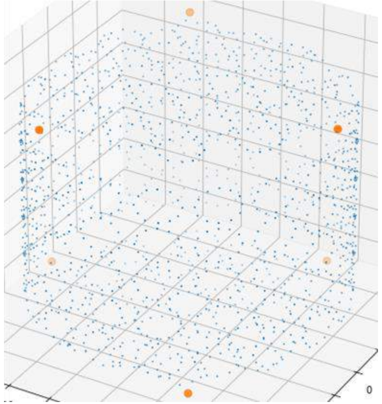
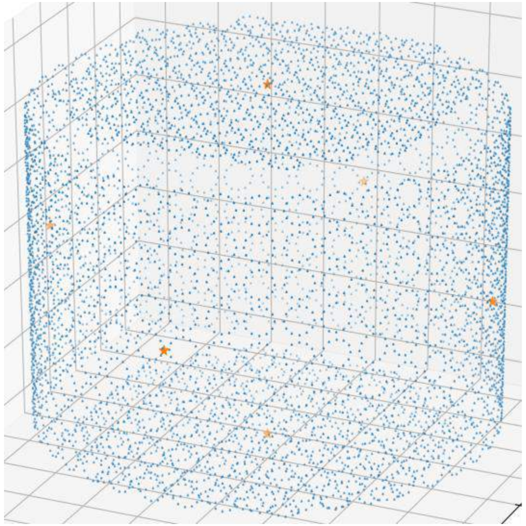
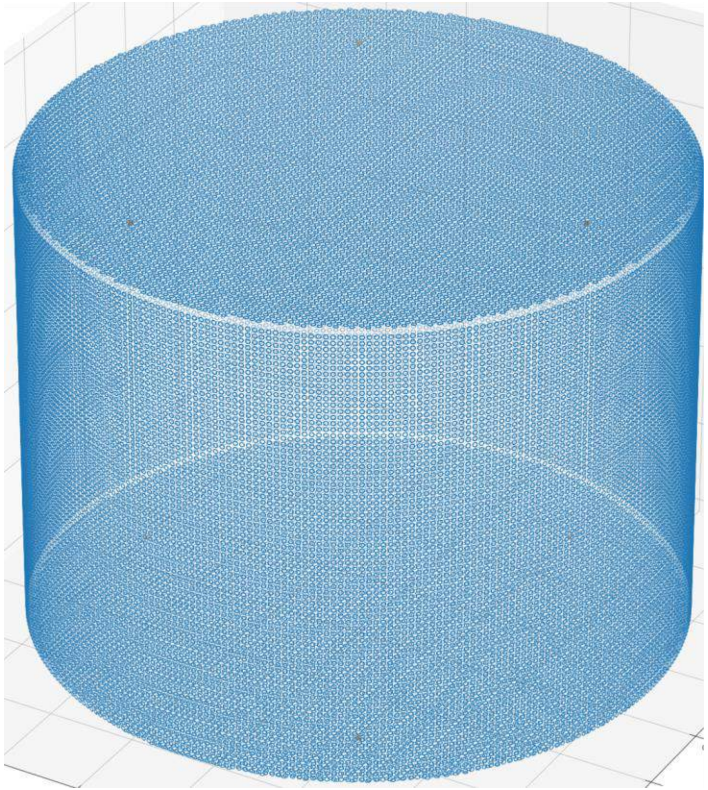


WCTE

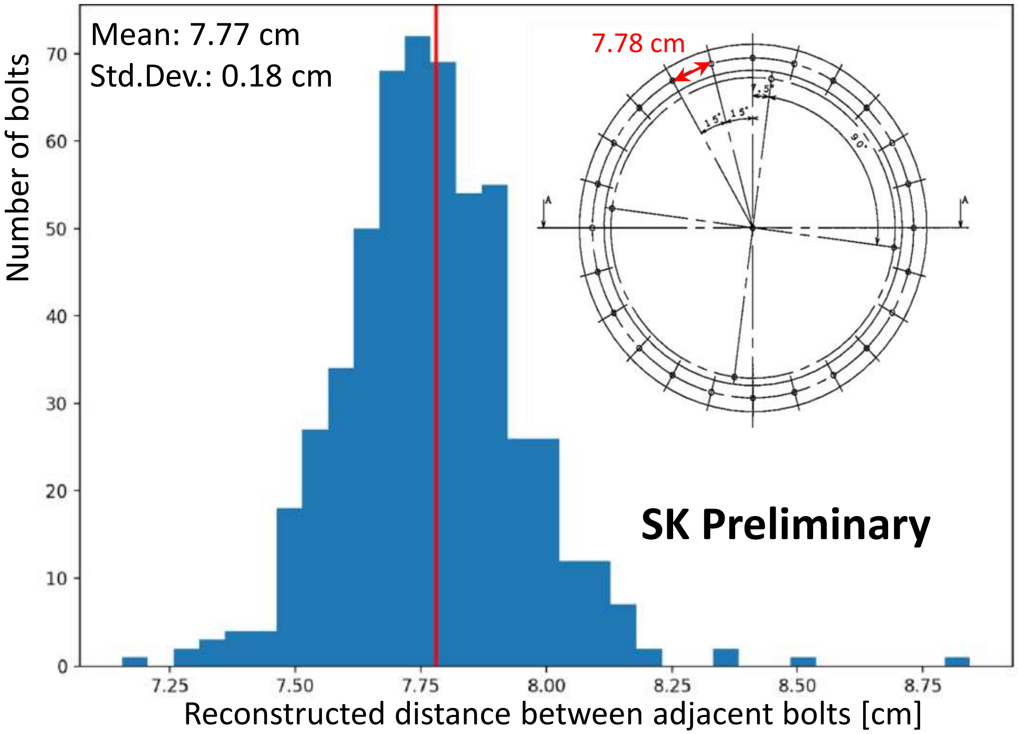


IWCD



Hyper-K

Results at Super-K



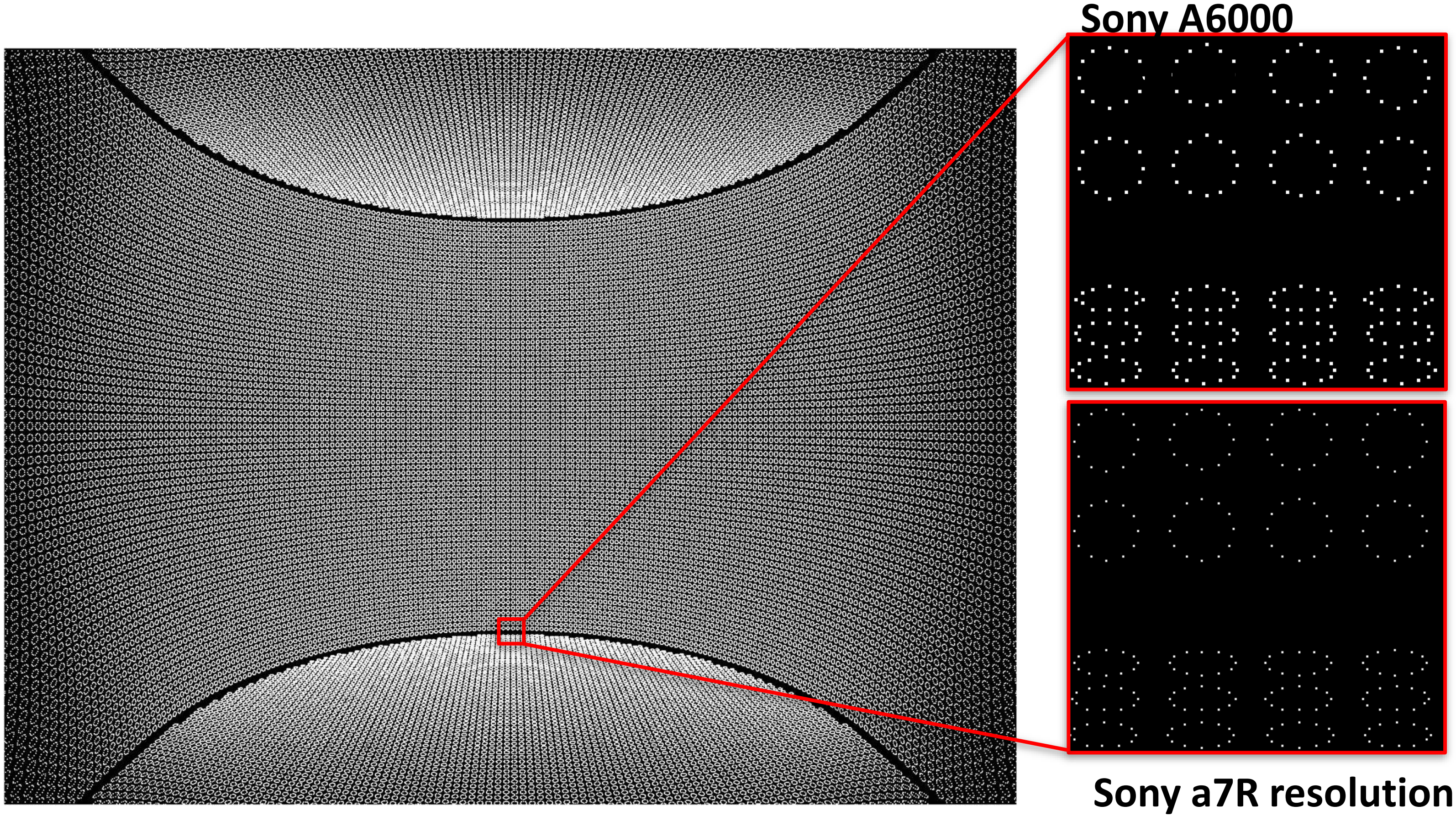
True distance between bolts should be ~7.78±0.02 cm

- Absolute scale is not determined by photogrammetry
- Look at spread of distances to estimate reconstruction errors
- (assume bolt distance is very precise in Super-K)

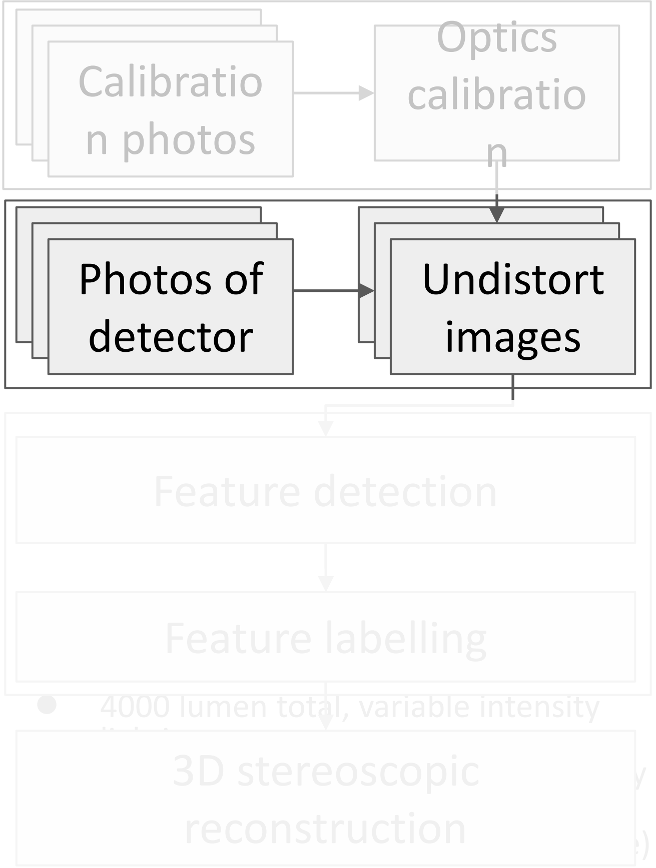
Spread suggests reconstructed distance errors of ~ 0.2 cm

But larger errors might exist over longer distance measurements

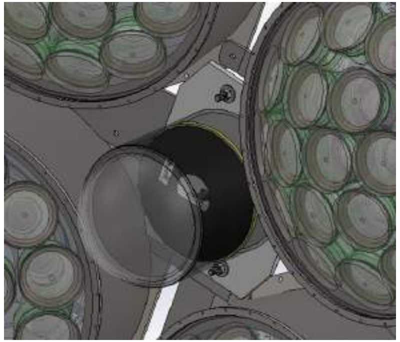
Simulations for future detectors



Photogrammetry data taking

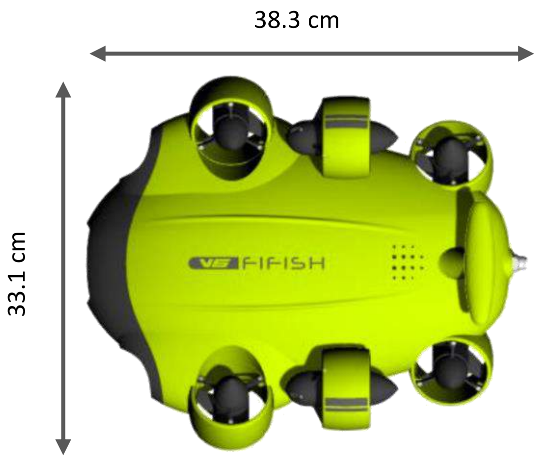


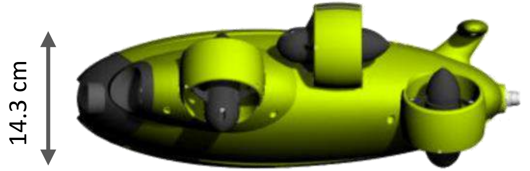
- Photographs taken using fixed or movable cameras inside detector
  - Fixed camera designs under development for future detectors WCTE, IWCD and Hyper-K
  - Remotely operated submersible used in Super-K for 5.5 hours during detector upgrade work in Feb. 2020



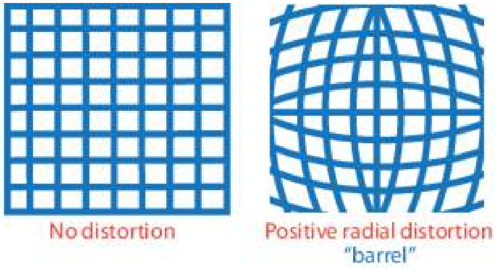
QYSEA FIFISH V6 Drone

- Relatively cheap (350000¥) consumer underwater drone
  - 100m depth rating
  - Small enough to fit through largest calibration port (~40 cm)
  - 6 DOF movement control (forward/backward, right/left, up/down)
    - Full orientation control (360° pitch, roll, yaw)
      - Can directly face end-caps; highly manoeuvrable
    - Depth and orientation sensors built in
  - Good low-light 12 MP camera sensor
    - Though flat lens port window not ideal for distortion
  - Sufficient (variable intensity) lighting: 4000 lumen total
  - Tethered for remote control and safety
    - Live stream to mobile device
  - 4 hour battery life (1 hour charge time)
- Two drones purchased
  - For backup in case of failure or recharging
- Company highly responsive and supportive
  - Quickly pushed firmware upgrades





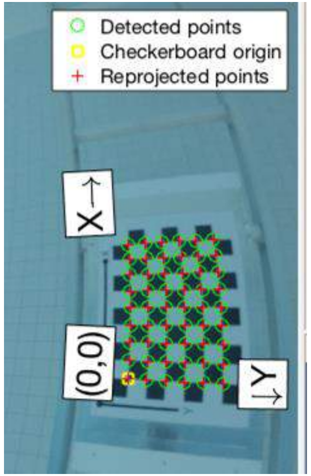
Camera Calibration

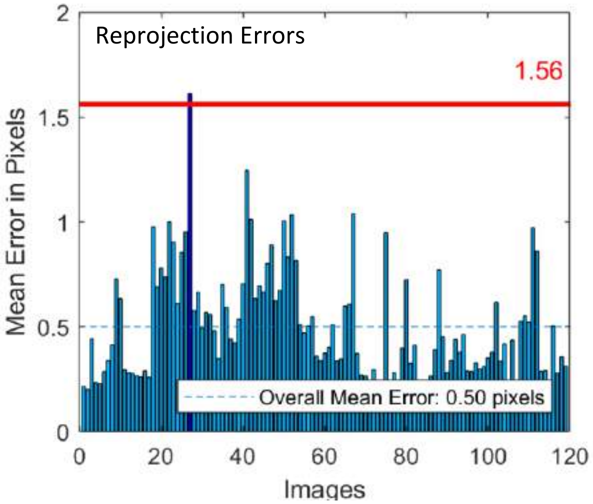


- Assume some distortion parameterization (e.g. fisheye) with free (intrinsic) parameters

- Now assume calibration pattern points are perfectly known, fitting only camera pose (extrinsic) and intrinsic parameters

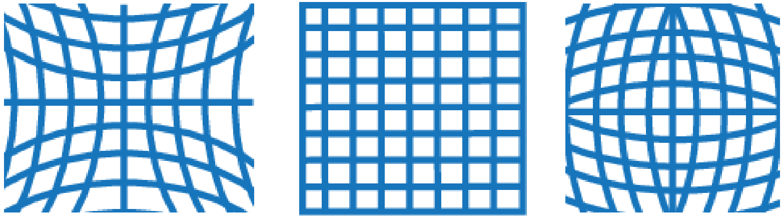
- Best mean reprojection error achieved = 0.35 pixels





Camera Calibration - Radial Coefficients

- Represent radial distortion of the lens



Negative radial distortion "pincushion" | No distortion | Positive radial distortion "barrel"

$$x_{\text{distorted}} = x(1 + k_1 {*} r^2 + k_2 {*} r^4 + k_3 {*} r^6)$$

$$y_{\text{distorted}} = y(1 + k_1 {*} r^2 + k_2 {*} r^4 + k_3 {*} r^6)$$

- k_1, k_2, k_3 = radial distortion coefficients
- x_distorted, y_distorted = distorted image points
- x, y = undistorted pixel locations
  - Translate pixel coordinates by optical centre
  - Divide by focal length [px]

$$R^2 = x^2 + y^2$$

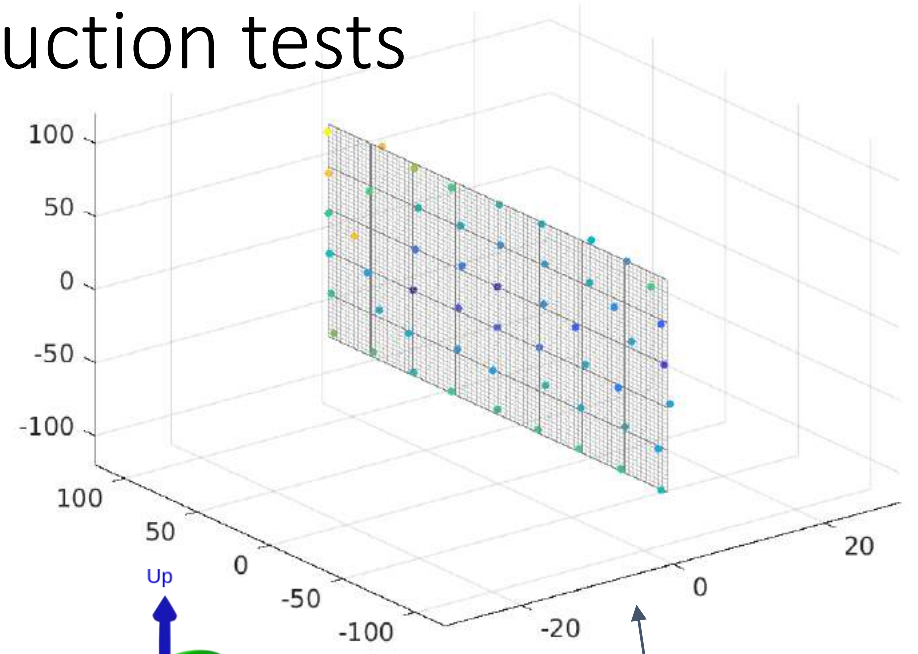
"Typically, two coefficients are sufficient for calibration. For severe distortion, such as in wide-angle lenses, you can select 3 coefficients to include k_3."
https://www.mathworks.com/help/vision/ug/camera-calibration.html

-0.25241	0.151602	-0.03072

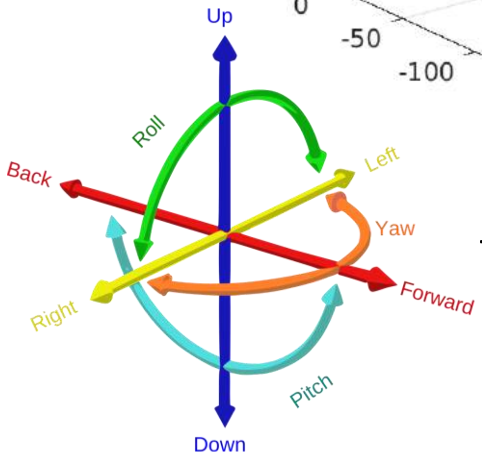
Photogrammetry reconstruction tests

To measure precision:

- Each point on pattern can be reconstructed anywhere in 3D space
  - Reconstruction does not force points to be in a plane, or to be in grid structure
- Rotate, translate and rescale to line up with known pattern
  - Kabsch algorithm finds optimal rotation / translation / scale to bring reconstructed points close to known (expected) points
  - Average position and scale is guaranteed to exactly match - photogrammetry is only sensitive to relative positions
- Distance between expected and reconstructed position of each grid point gives errors on 3D positions



Note: stretched axis scale to exaggerate errors



3D reconstruction: Absolute scale

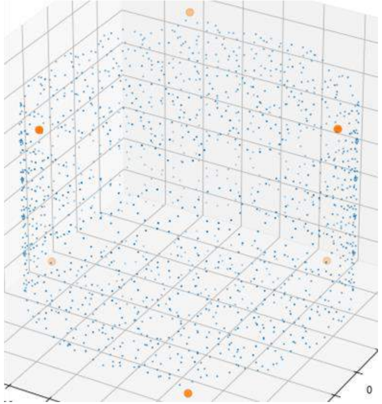
Absolute scale is not determined by photogrammetry

- Re-scaling entire geometry leaves all photos unchanged
  - Impossible to reconstruct scale without some reference
- Part of Kabsch algorithm for comparing reconstructed to true geometry rescales coordinates, so scale of 3D reconstruction is arbitrary
- But we could want to reconstruct the scale, e.g. to check FV of SK
- Use some known lengths in images to calibrate the scale
  - e.g. the known distance between bolts, or known light injector positions
  - Ideally we rescale using many known distances (many adjacent bolts, and light injector positions, and ...)
- Then remove the rescaling from Kabsch algorithm and just rotate/translate reconstructed geometry to compare to true geometry

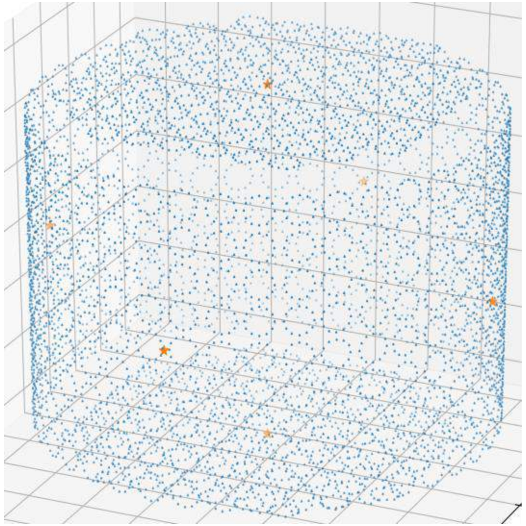
Photogrammetry simulations

Simulation framework to test photogrammetry configurations

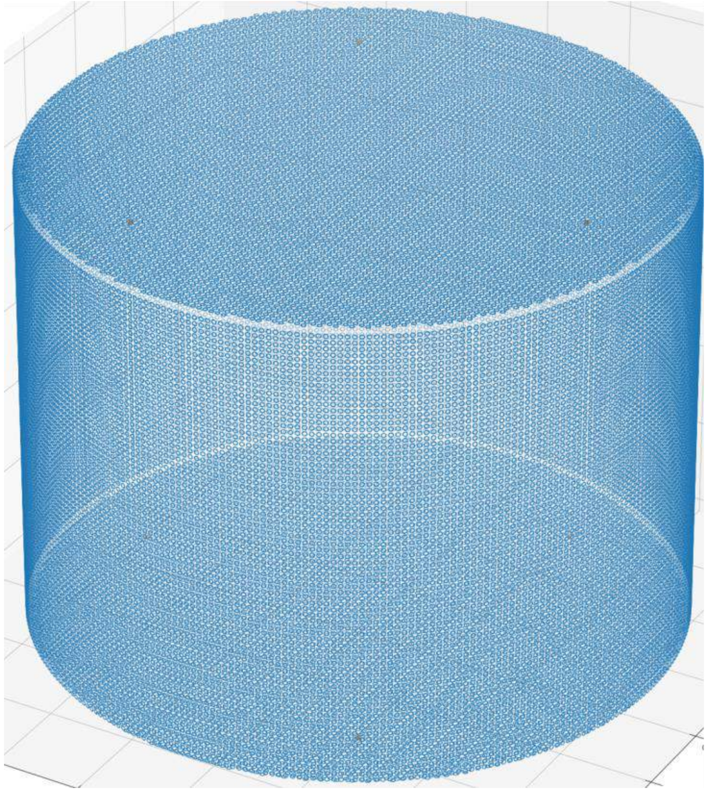
- Simulate images for different detector geometries & camera configurations
- Calculate expected 3D reconstruction precision



WCTE



IWCD



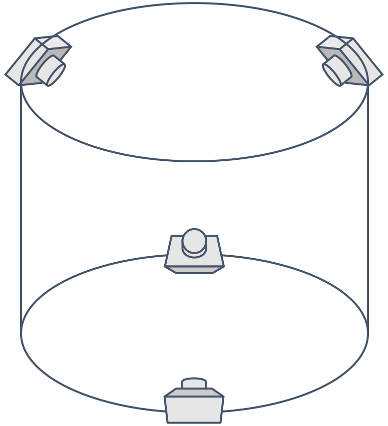
Hyper-K

Photogrammetry simulations

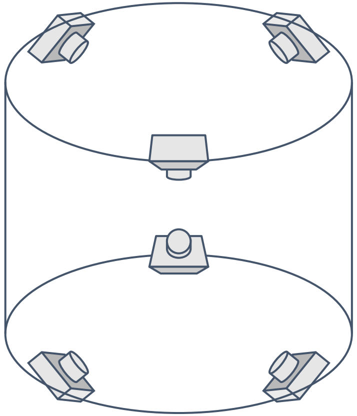
Choice of camera specs:

- GoPro Hero4 Black: Calibrated underwater
- Sony Alpha A6000 (24MP): Calibrated in air
- Sony α7R IV (61MP): Assume same as A6000 with increased image resolution

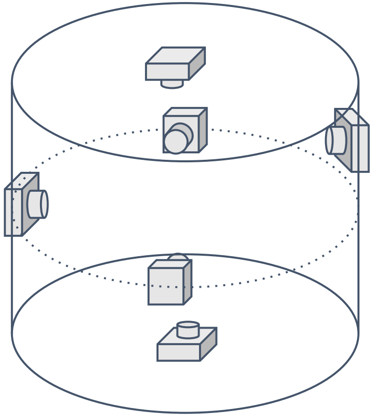
Change number and positions of cameras, e.g.:



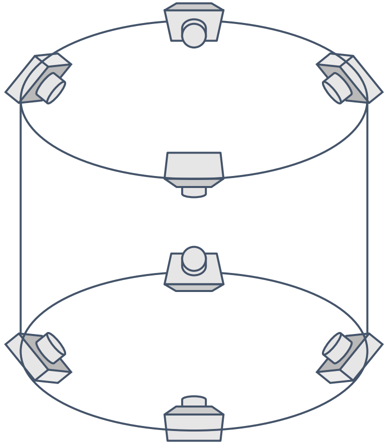
4 cameras



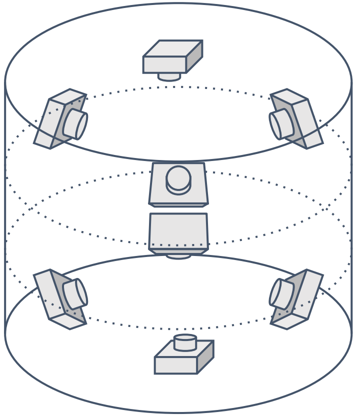
6 cameras config A



6 cameras config B



8 cameras config A

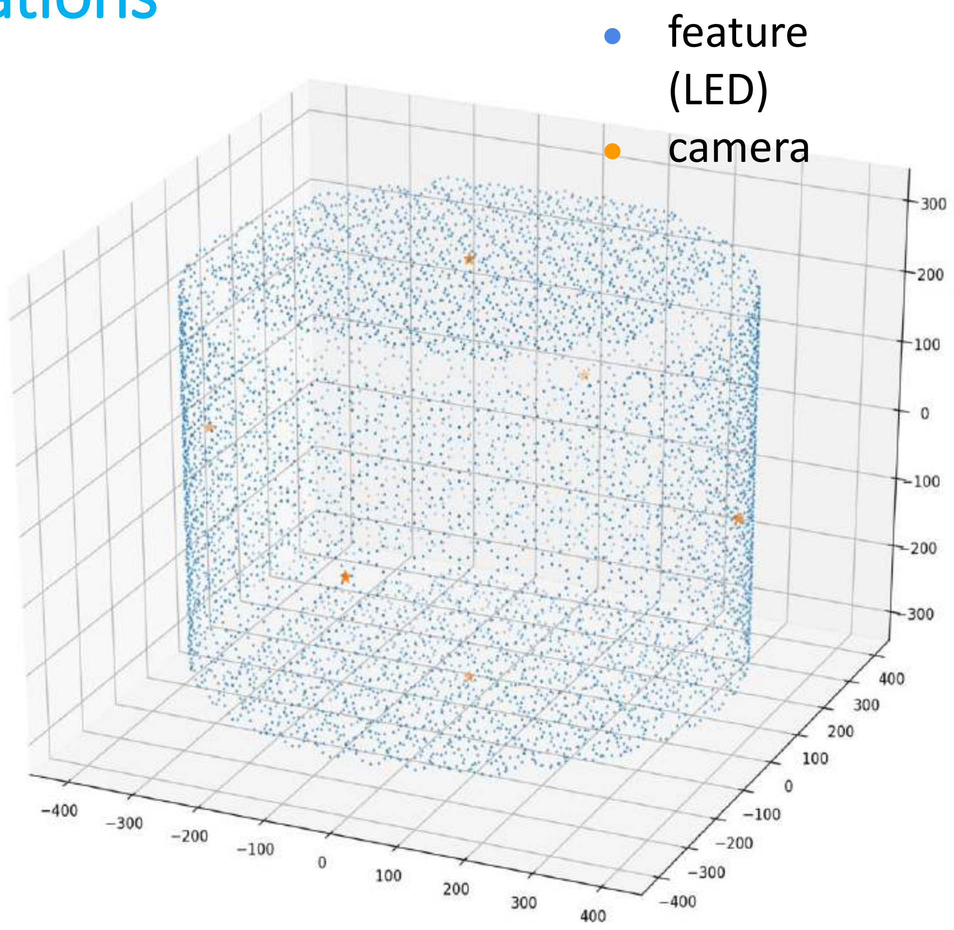


8 cameras config B

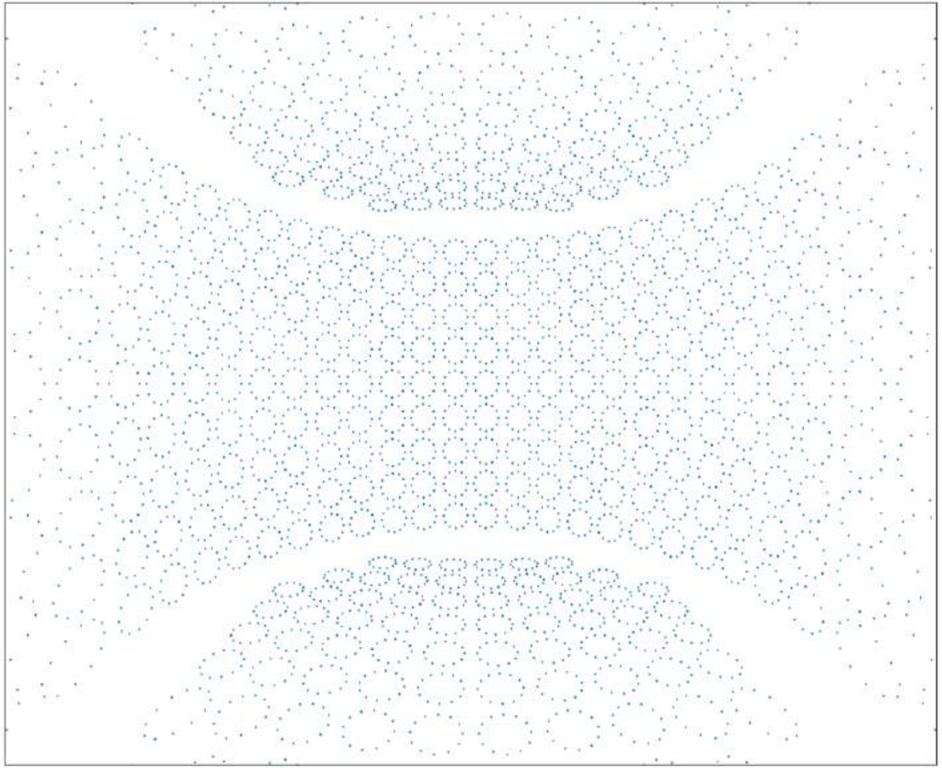
IWCD photogrammetry simulations

IWCD Simulations

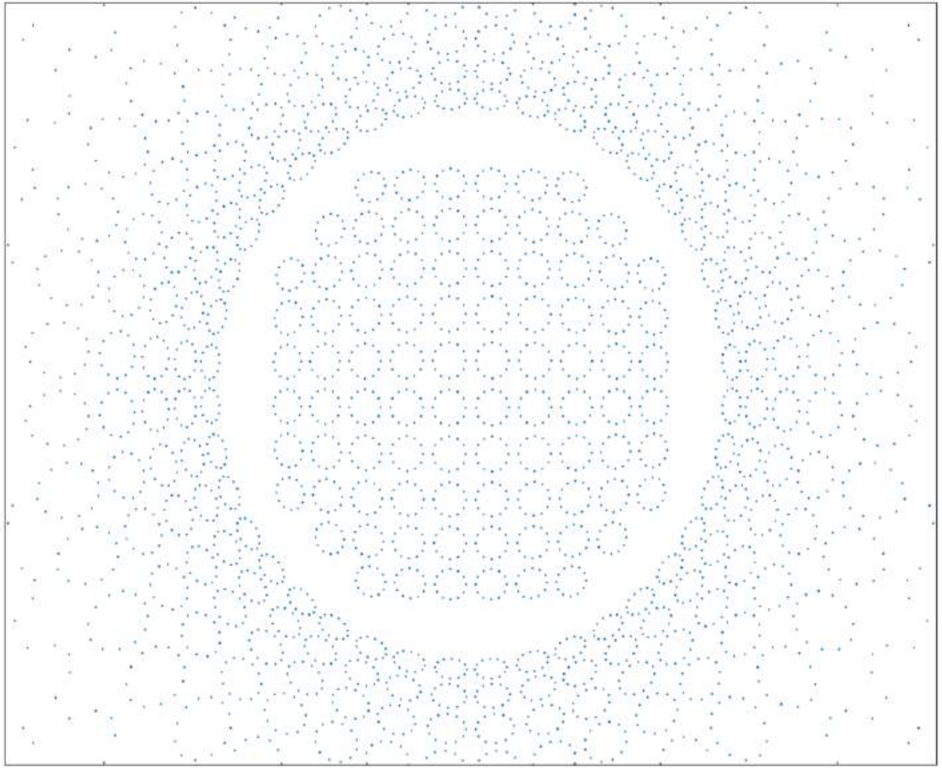
- Assume 6 fixed cameras (2 on end-caps, 4 around barrel)
- LEDs built into mPMTs
    - Test with 12, 6, 4 or 3 LEDs per mPMT
- Each LED visible from minimum of 3 cameras
- Smear 2D image points for camera resolution and feature finding error
- Simulated images & applied photogrammetry reconstruction
    - Find LED positions
    - Fint mPMT centre position & orientation



IWCD photogrammetry simulations



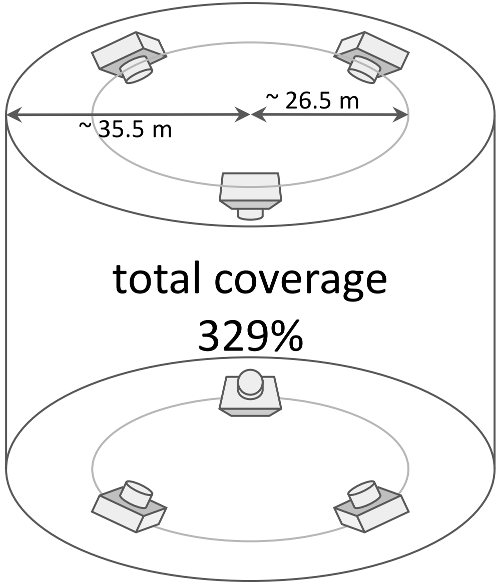
View from barrel camera (12 LEDs per mPMT)



View from end-cap camera (12 LEDs per mPMT)

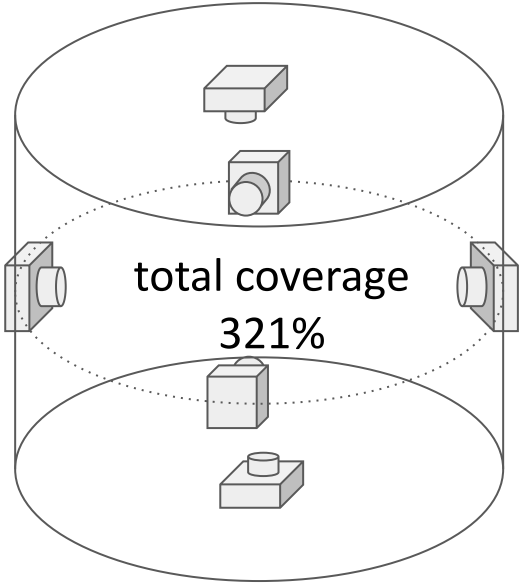
HK Photogrammetry

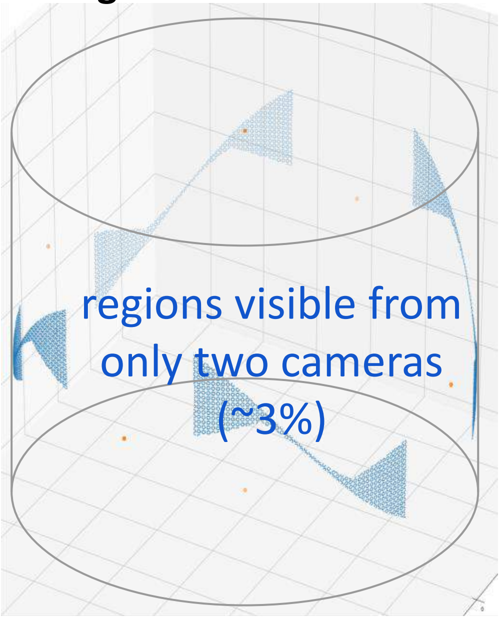
Minimal 6-camera configuration



- All parts of detector visible from at least 3 cameras
- Tilted cameras increase feature identification difficulty

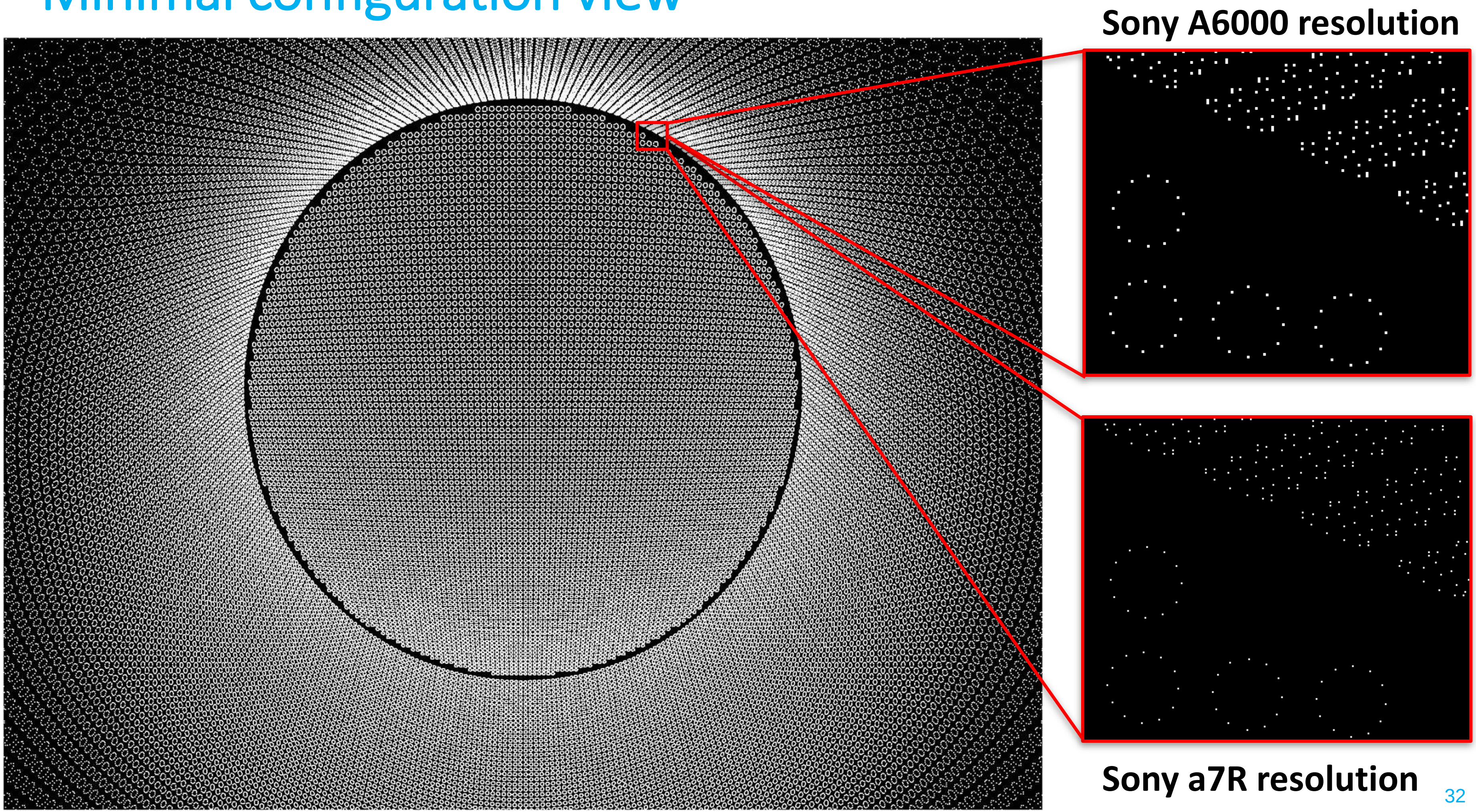
Alternative 6-camera configuration



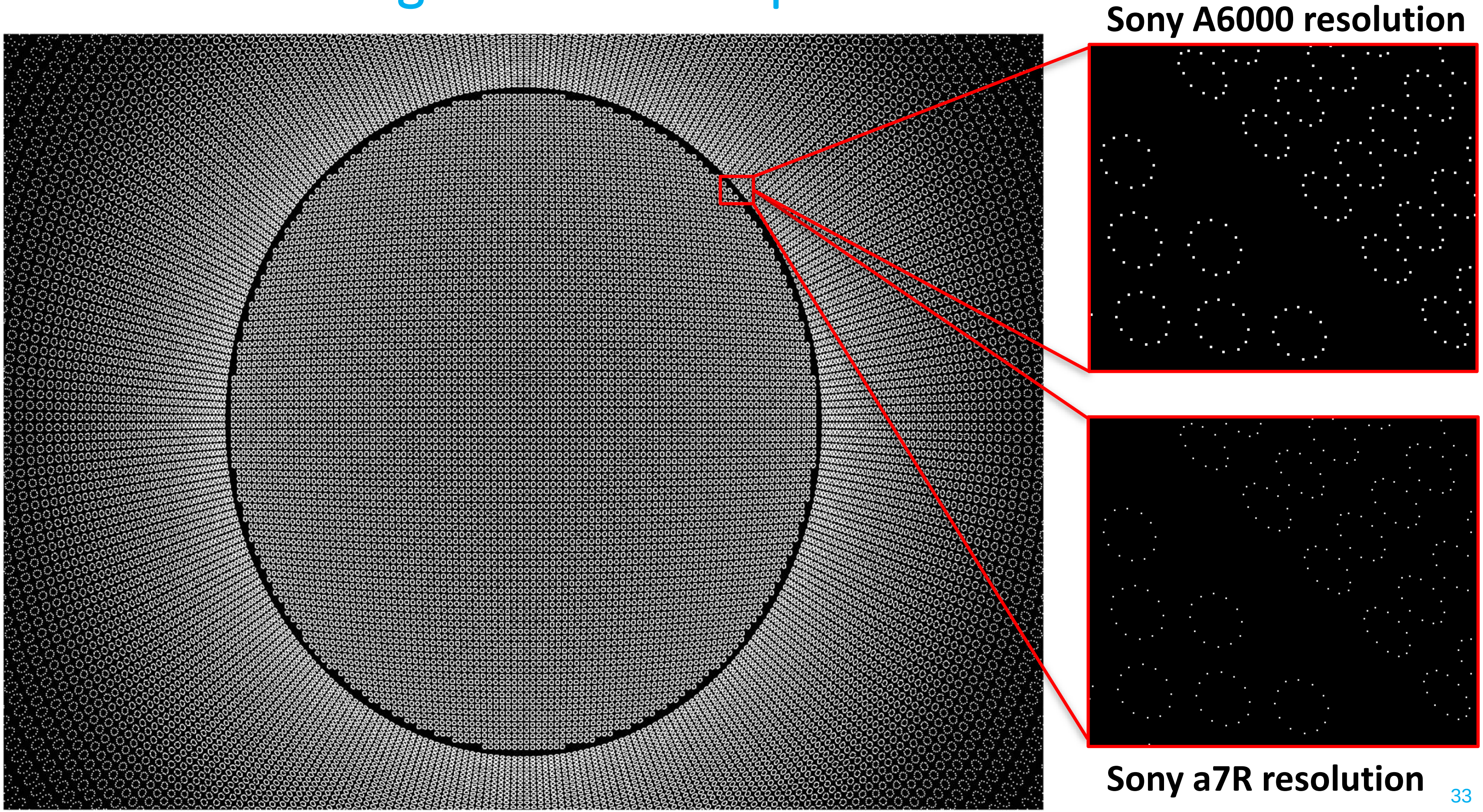


- Lose redundancy in regions visible from only two cameras
- Un-tilted cameras help feature identification

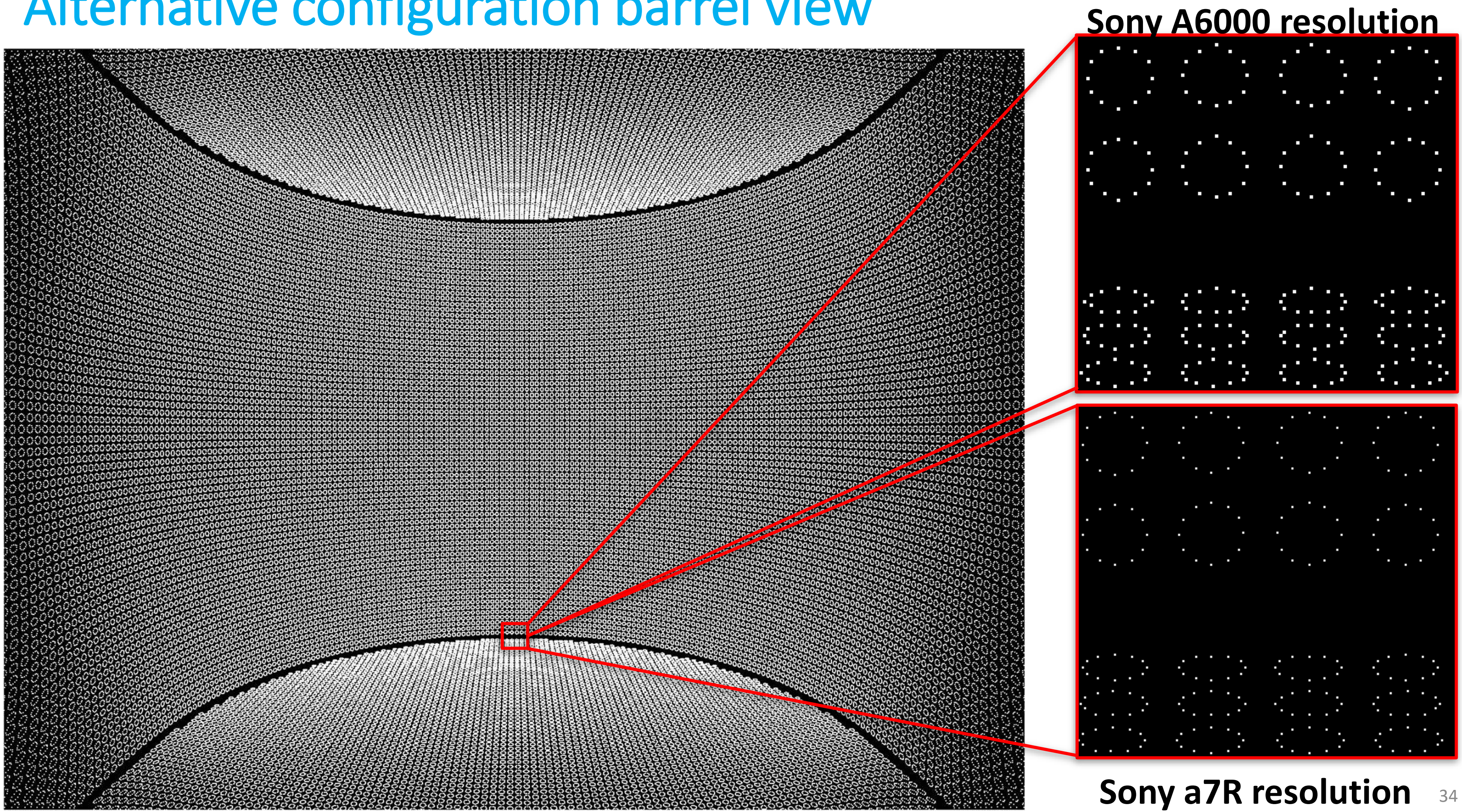
Minimal configuration view



Alternative configuration end-cap view



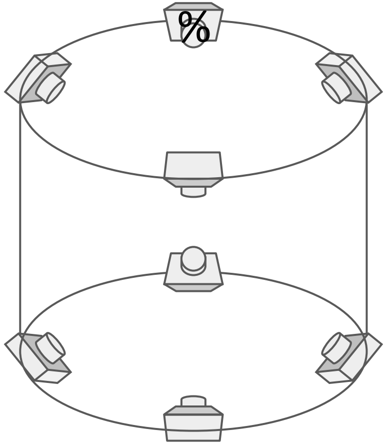
Alternative configuration barrel view



HK Photogrammetry

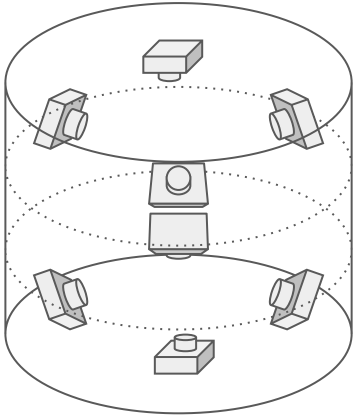
- Can add more cameras to increase redundancy
- For positions, trade-off increased coverage vs easier feature finding
- Need simulations to check visibility of deployed calibration sources

Total coverage = 519 %



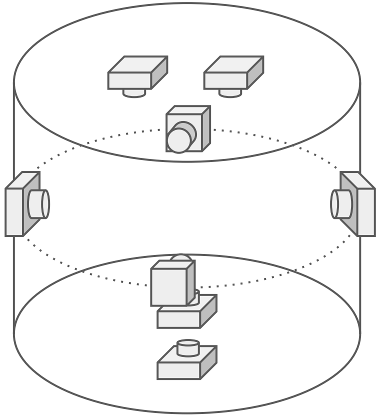
8 cameras config A

Total coverage = 436 %



8 cameras config B

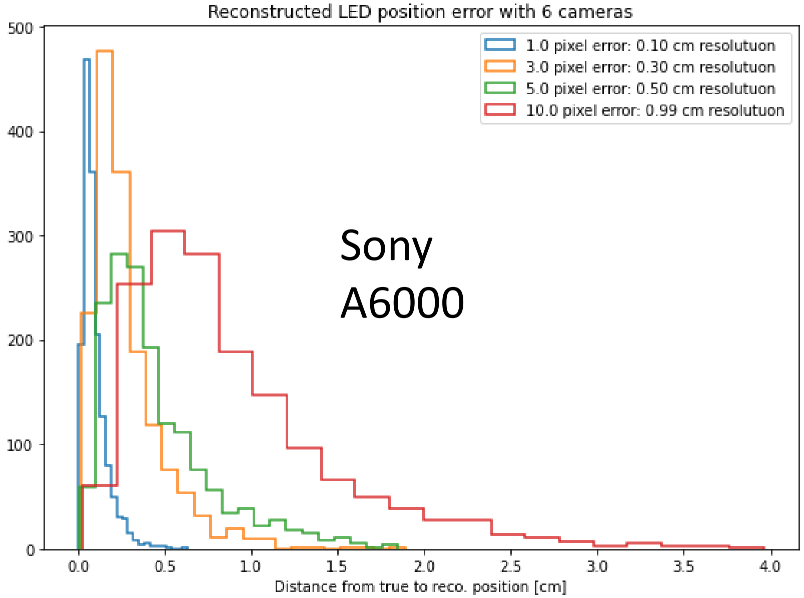
Total coverage = 408 %

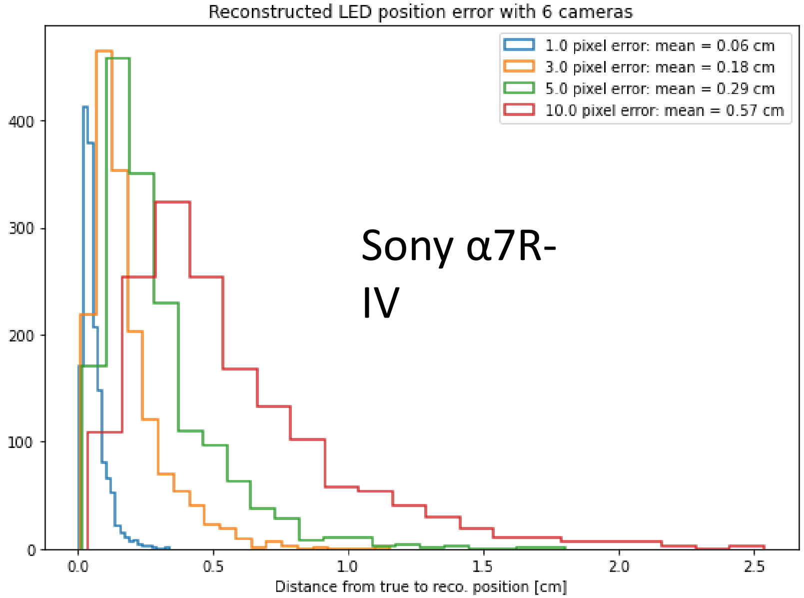


8 cameras config C

Example LED position resolutions for 6A config

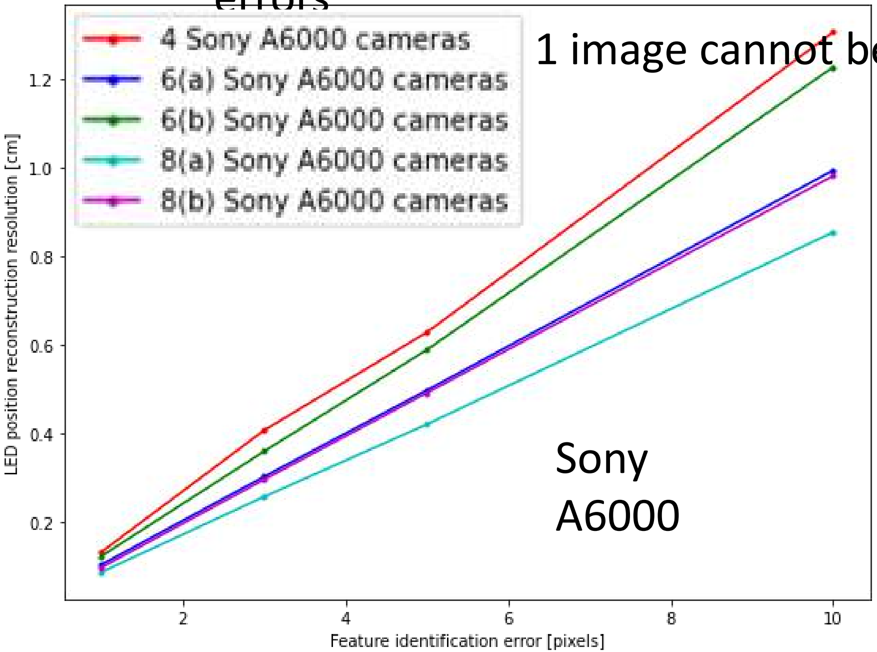
- 1-sigma resolution defined as 68th percentile of distance from true to reconstructed position
- Good resolution (< 1 cm) even with 10 pixel random smearing
- Resolutions improve with camera resolution, as expected
    - Fixed pixel size smearing might unrealistically favour higher resolution
        - Systematic feature identification errors may be larger in pixel size for higher res images

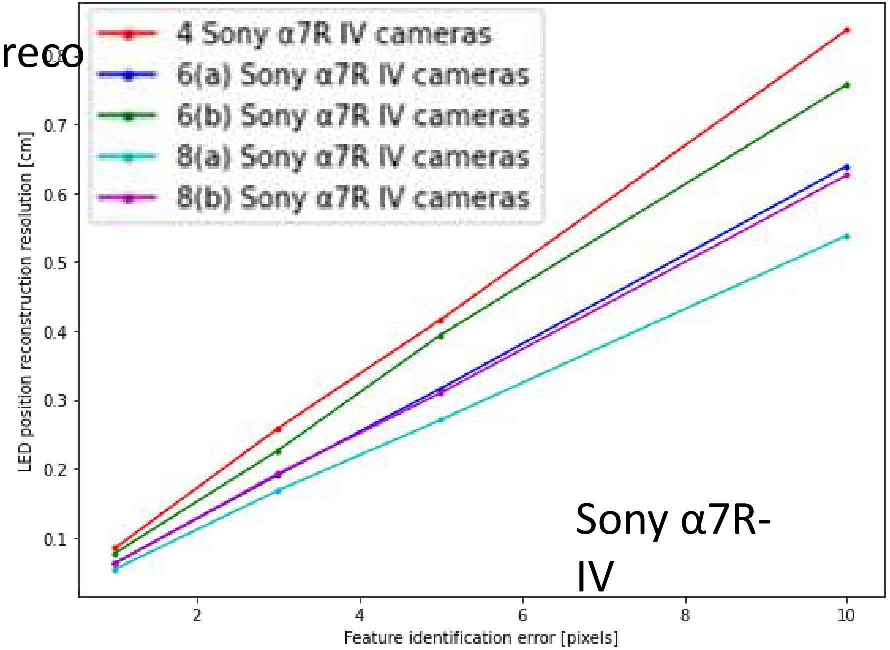




- ‘B’ configs perform worse than ‘A’ configs
  - As expected due to lower feature overlap
  - ‘A’ configs preferred, if feature identification & labelling is not too difficult
- 4 camera config or 6B config might not be enough
  - Quite precise position & direction of cameras required to ensure all features visible in 2 images
  - Reliant on using features at edge of image where there’s likely larger systematic errors

1 image cannot be reco





mPMT centre and orientation resolutions generally follow the LED position resolutions

Typically get < 0.5 cm position resolution, < 1 degree orientation resolution