



Enhancing 3D Visual Odometry with Single-Camera Stereo Omnidirectional Systems

Thesis Defense

Carlos Jaramillo
Spring 2018



INTRODUCTION

**Enhancing 3D Visual Odometry with
Single-Camera Systems**

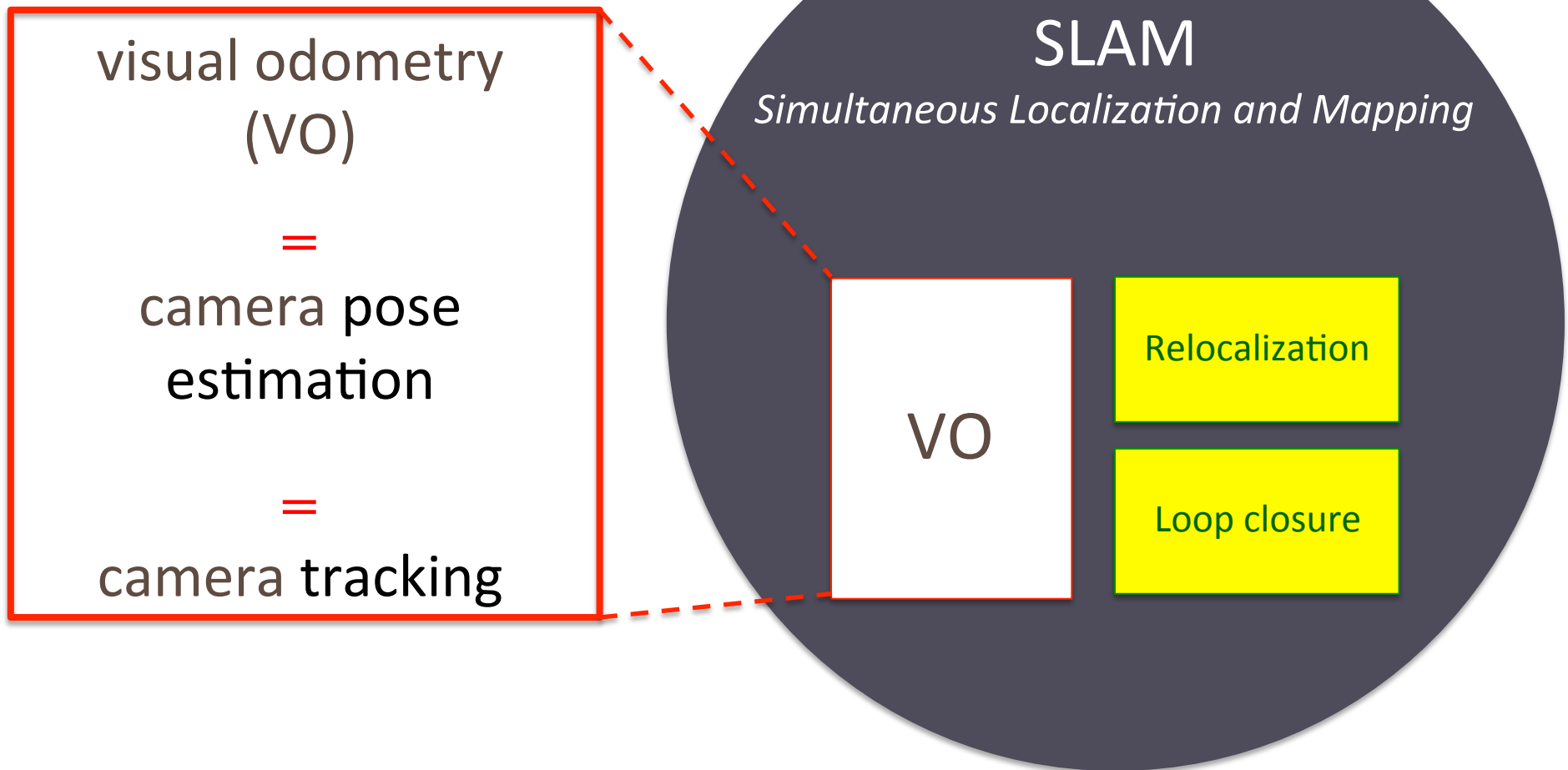




Goal: Enhancing Visual Odometry

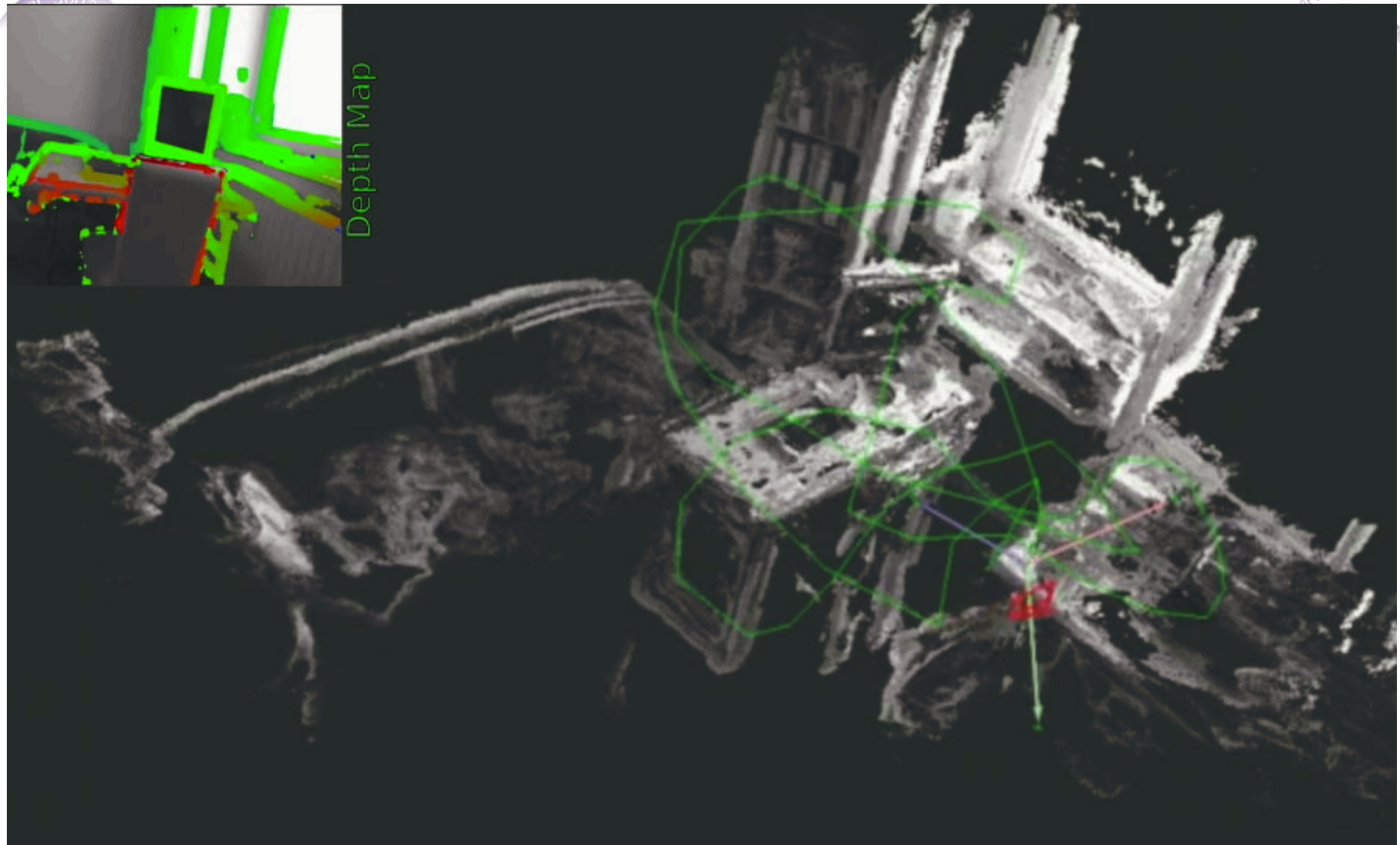


<Intro> <SOS> <GUMS> <VO>



Visual Odometry Example

<Intro> <SOS> <GUMS> <VO>





Goal Oriented Contents

<Intro> <SOS> <GUMS> <VO>



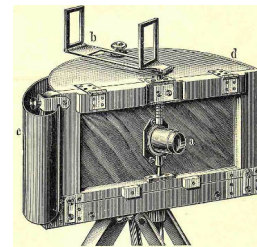
1. Problem Motivation: Omnidirectional Vision
2. Design of the Single-Camera Stereo Omnidirectional System (SOS)
3. Projection model (GUMS) and calibration
4. Visual odometry (VO) with Single-Camera SOS

<Intro> <SOS> <GUMS> <VO>

- 3-D world ↔ Surround Vision



- 3-D world \leftrightarrow Surround Vision
- Eye geometry of insects
 - 360° azimuthal field of view.
- **Technology:** Panoramic Vision via
 - Slit photography (1843)



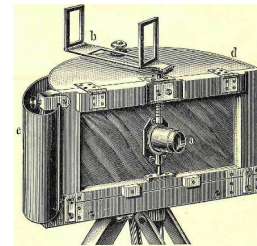
Puchberger's
first panoramic-camera

View from the top of
Lookout Mountain, TN,
Albumen prints,
February, 1864,
by *George N. Barnard*



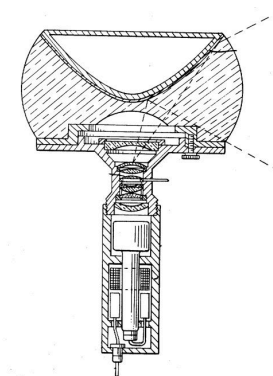
Public Domain, <https://commons.wikimedia.org/w/index.php?curid=85275>

- 3-D world \leftrightarrow Surround Vision
- Eye geometry of insects
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- **Technology:** Panoramic Vision via
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Puchberger's first panoramic-camera

- Catadioptric Sensors (1911)
 - Cata (Mirror) + Dioptric (Lenses)
- Wide-angle Lenses



Rees hyperbolic ODVS (1970)

Metric Range Perception Devices

<Intro> <SOS> <GUMS> <VO>

Active
Time-of-Flight

- Sonars (Ultrasonic)



- Laser Range Finders (LIDAR: Light Detection And Ranging)



- SwissRanger 3D camera



- RGB-D Sensors

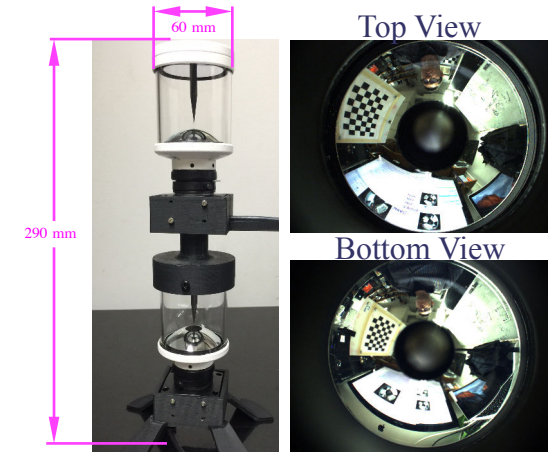


Passive

- Stereo Cameras



- **Stereo Catadioptrics** (Mirrors + lenses)





SINGLE-CAMERA STEREO OMNIDIRECTIONAL SYSTEM (SOS)

Peer-reviewed articles:

Spherical SOS:

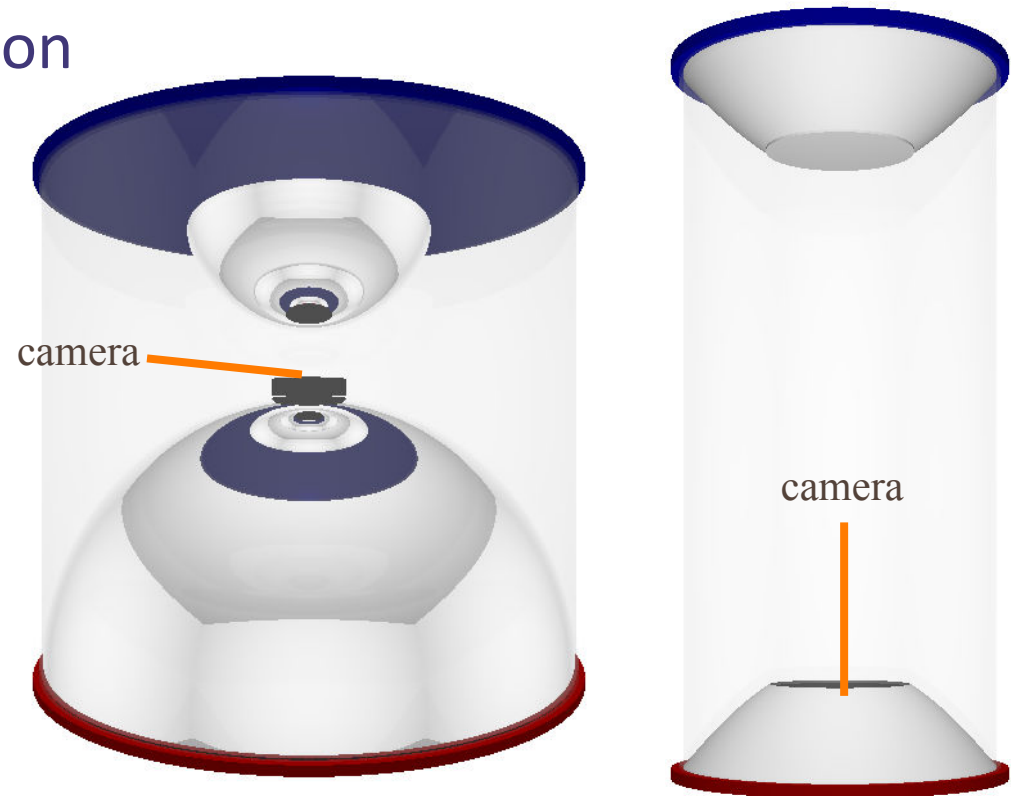
Igor Labutov, **Carlos Jaramillo**, and Jizhong Xiao.
“*Generating near-spherical range panoramas by fusing optical flow and stereo from a single-camera folded catadioptric rig.*”
Machine Vision and Applications, 24(1):1–12, 9 2011.

Hyperbolic SOS:

Carlos Jaramillo, Roberto G Valenti, Ling Guo, and Jizhong Xiao.
“*Design and Analysis of a Single-Camera Omnistereo Sensor for Quadrotor Micro Aerial Vehicles (MAVs).*”
Sensors, 16(2):217, 1 2016. ISSN 1424-8220

- **Design goal:**
 - Omnidirectional 3D Vision with a **single camera** + **two curved mirrors**
- **Design advantages:**
 - Low cost (\$ and ⚡)
 - Light weight (portable)
 - Wide field-of-view
 - Passive sensing

“Folded” SOS Configurations



Spherical mirrors

Hyperbolic mirrors

Single-Camera SOS

<Intro> <**SOS**> <GUMS> <VO>

Omnistereo Intuition



Single-Camera SOS

<Intro> <**SOS**> <GUMS> <VO>

Omnistereo Intuition



Single-Camera SOS

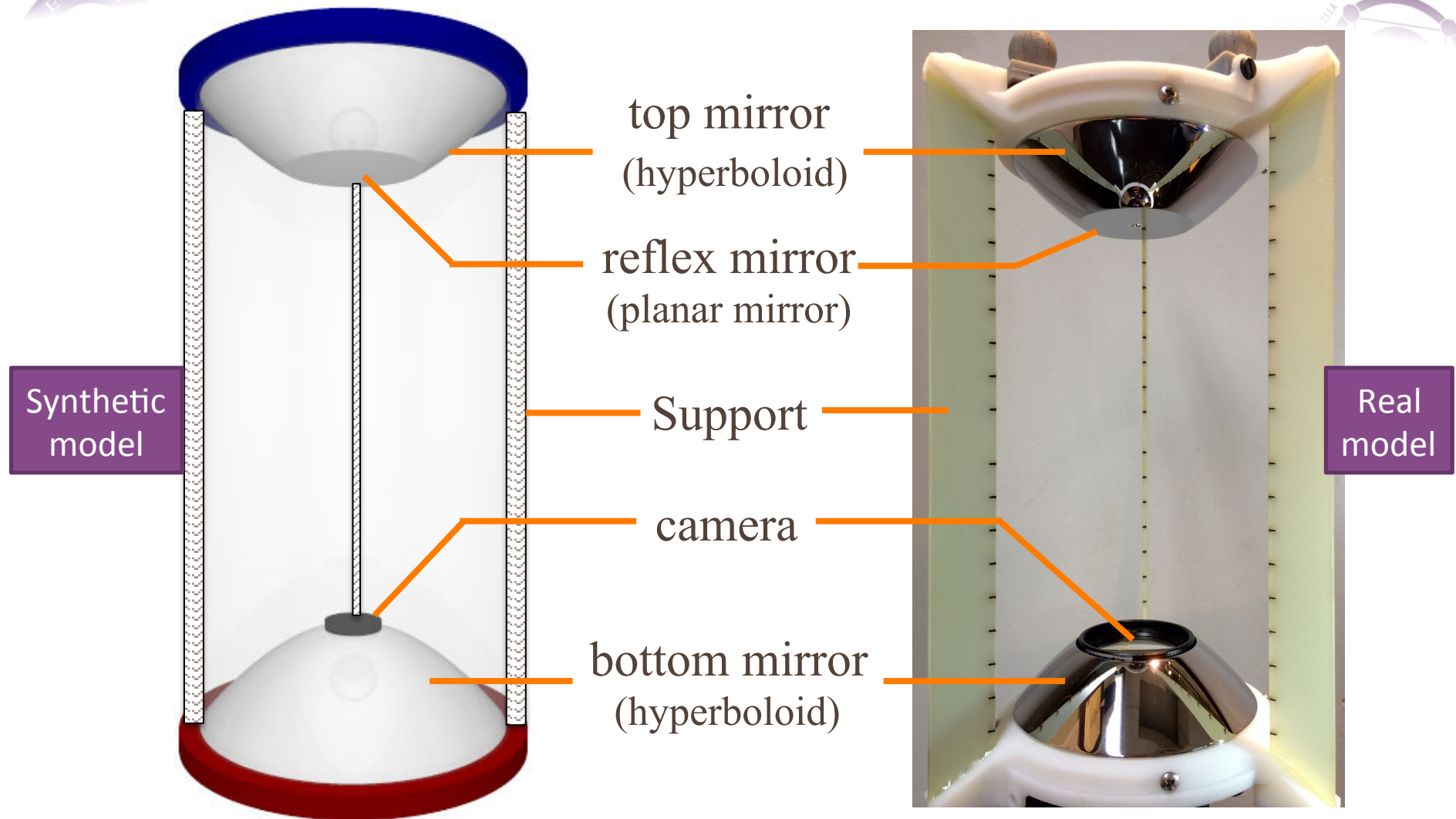
<Intro> <**SOS**> <GUMS> <VO>

Omnistereo Intuition

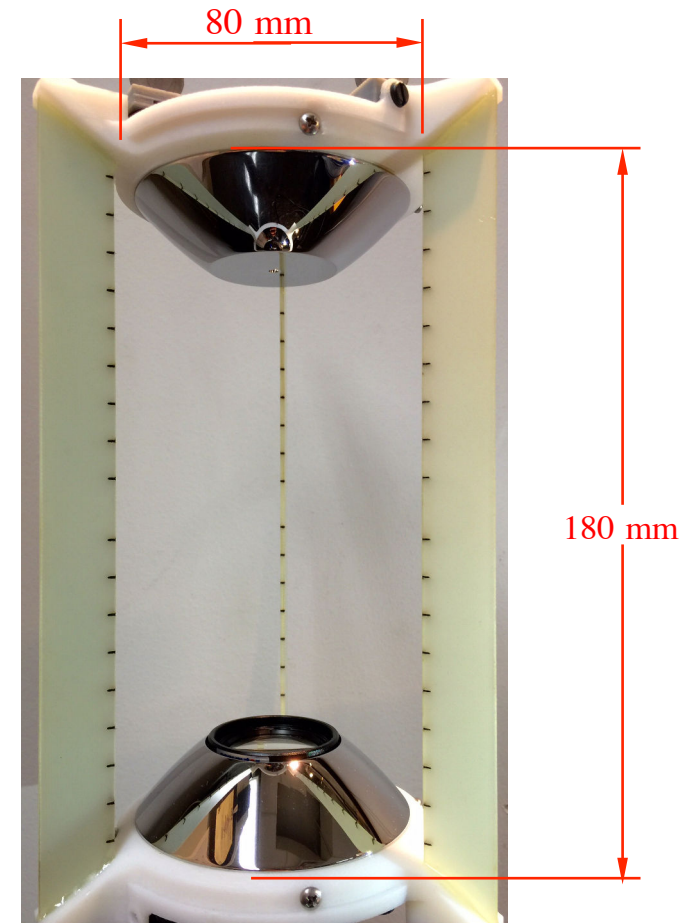


Hyperbolic Single-Camera SOS

<Intro> <**SOS**> <GUMS> <VO>



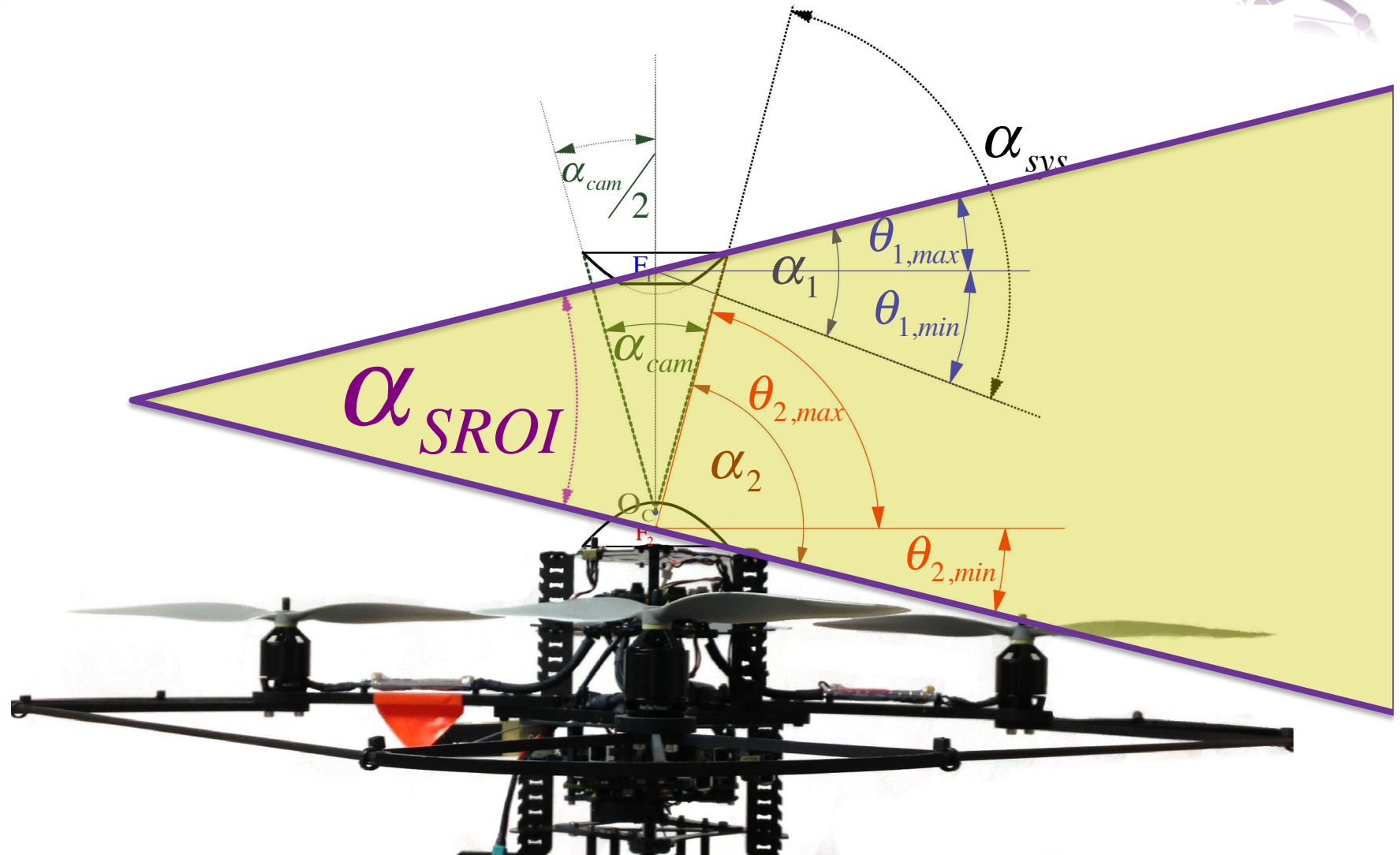
- **Design goal:**
 - Omnidirectional stereo vision with **configurable** stereo region (SROI)
- **Design pros:**
 - Low radial distortion
 - Central (SVP), or slighty-central (real)
 - Optimal FOV (SROI) + baseline
- **Design cons**
 - Custom hyperbolic mirrors
 - Hard to assemble
 - cannot satisfy the theoretical SVP
 - misalignment issues



baseline \approx 150 mm

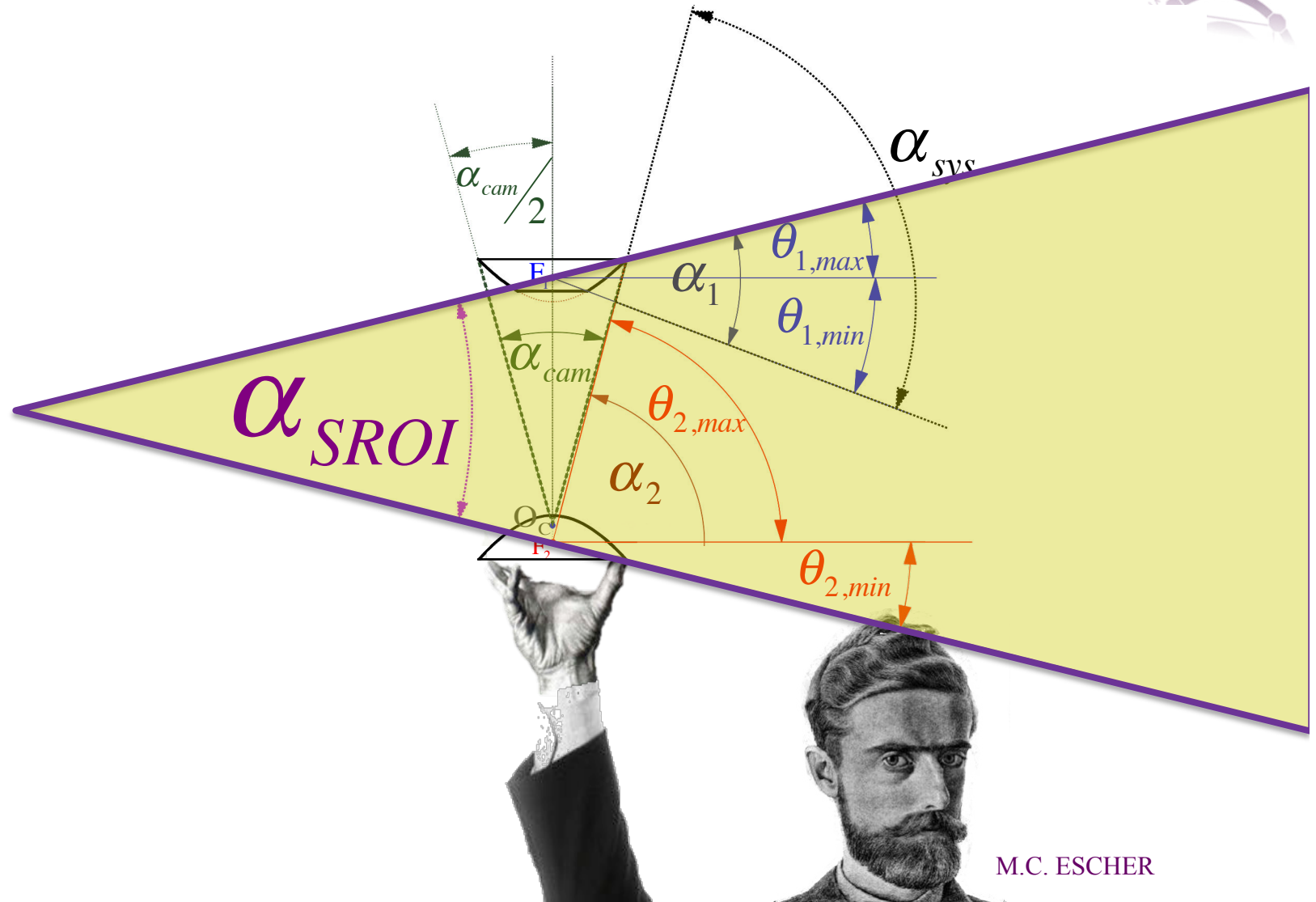
Hyperbolic SOS: Field-of-View

<Intro> <**SOS**> <GUMS> <VO>



Hyperbolic SOS: Field-of-View

<Intro> <**SOS**> <GUMS> <VO>

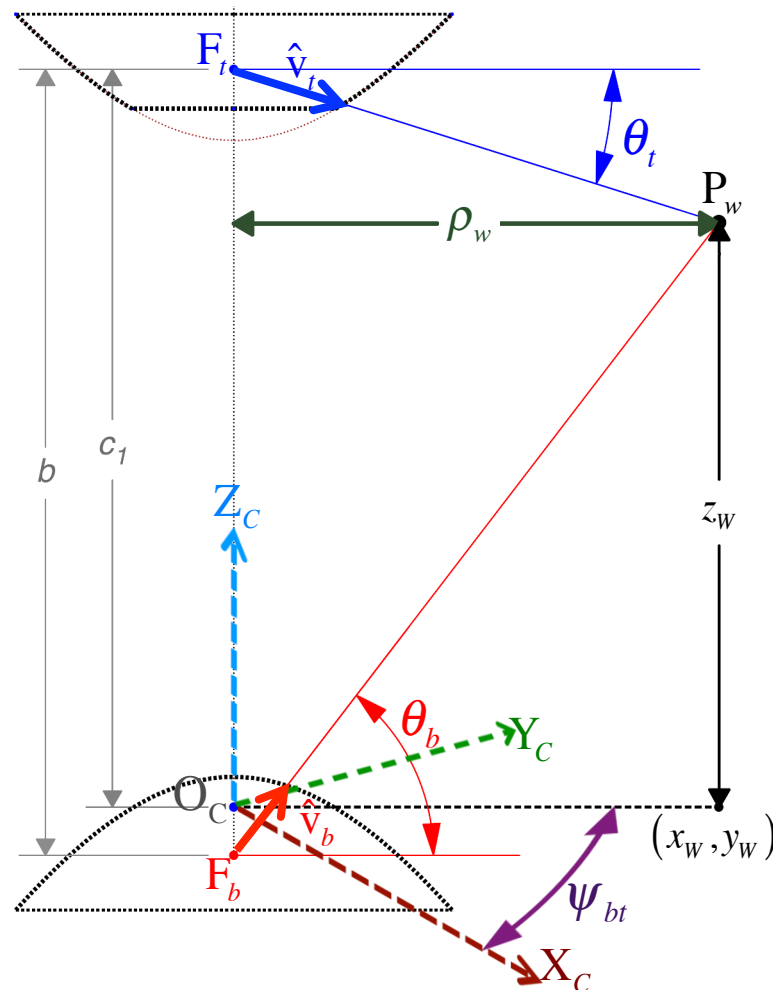


M.C. ESCHER

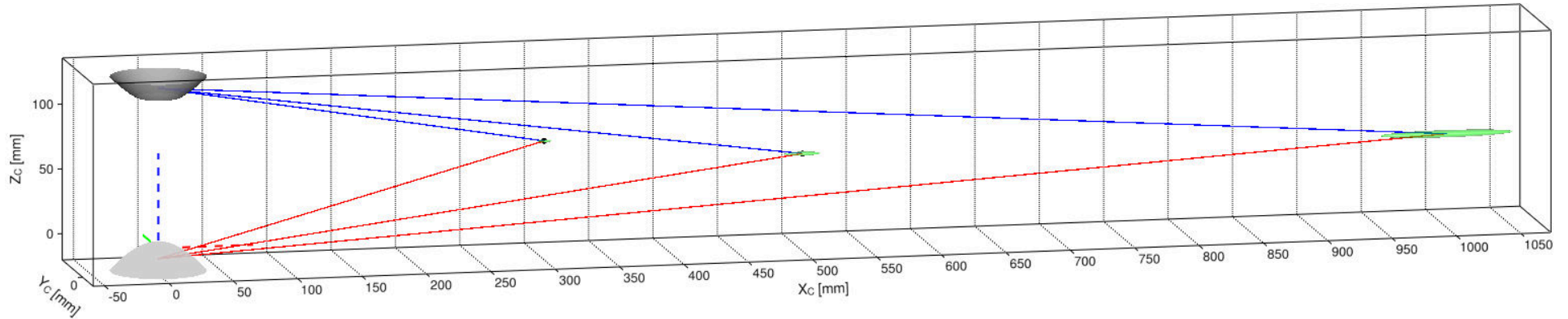
Hyperbolic SOS: Triangulation

<Intro> <**SOS**> <GUMS> <VO>

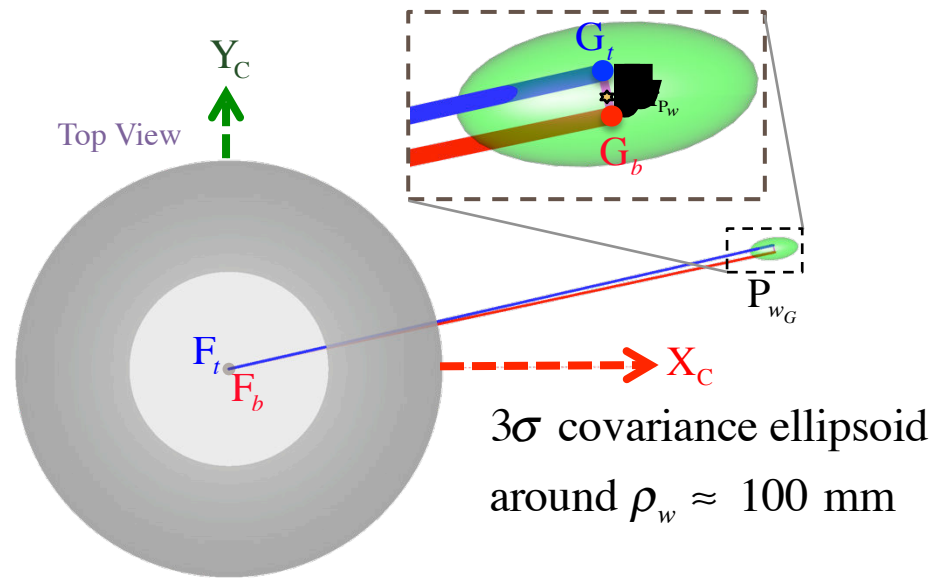
Goal: Back-projected direction vectors \hat{v}_t and \hat{v}_b of a point's correspondences in the image are triangulated as P_w



Uncertainty ellipsoids (viz at 1-sigma) for triangulated points at ranges $\rho_w \approx \{0.3, 0.5, 1.0\}$ meters



For a std. dev. of 1 pixel
in the image correspondences



Hyperbolic SOS: Parameters

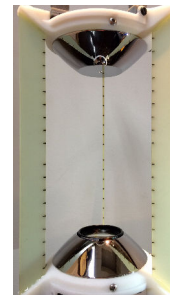
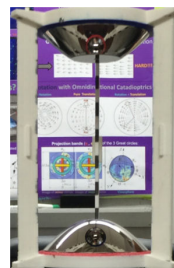
<Intro> <**SOS**> <GUMS> <VO>

Rig Geometric Parameters (Theoretical Values)

Parameter	Dimension on Rig Type	
	Near-Sighted	Far-Sighted
r_{sys} [mm]	37.0	40.0
r_{ref} [mm]	17.2	19.0
r_{cam} [mm]	7.0	18.0
b [mm]	131.6	150.0
h_{sys} [mm]	150.0	176.6
α_{sys} [°]	66.8	40.9
α_{SROI} [°]	25.0	33.5
ρ_{min} [mm]	65.0	250.0

Min Range [mm]

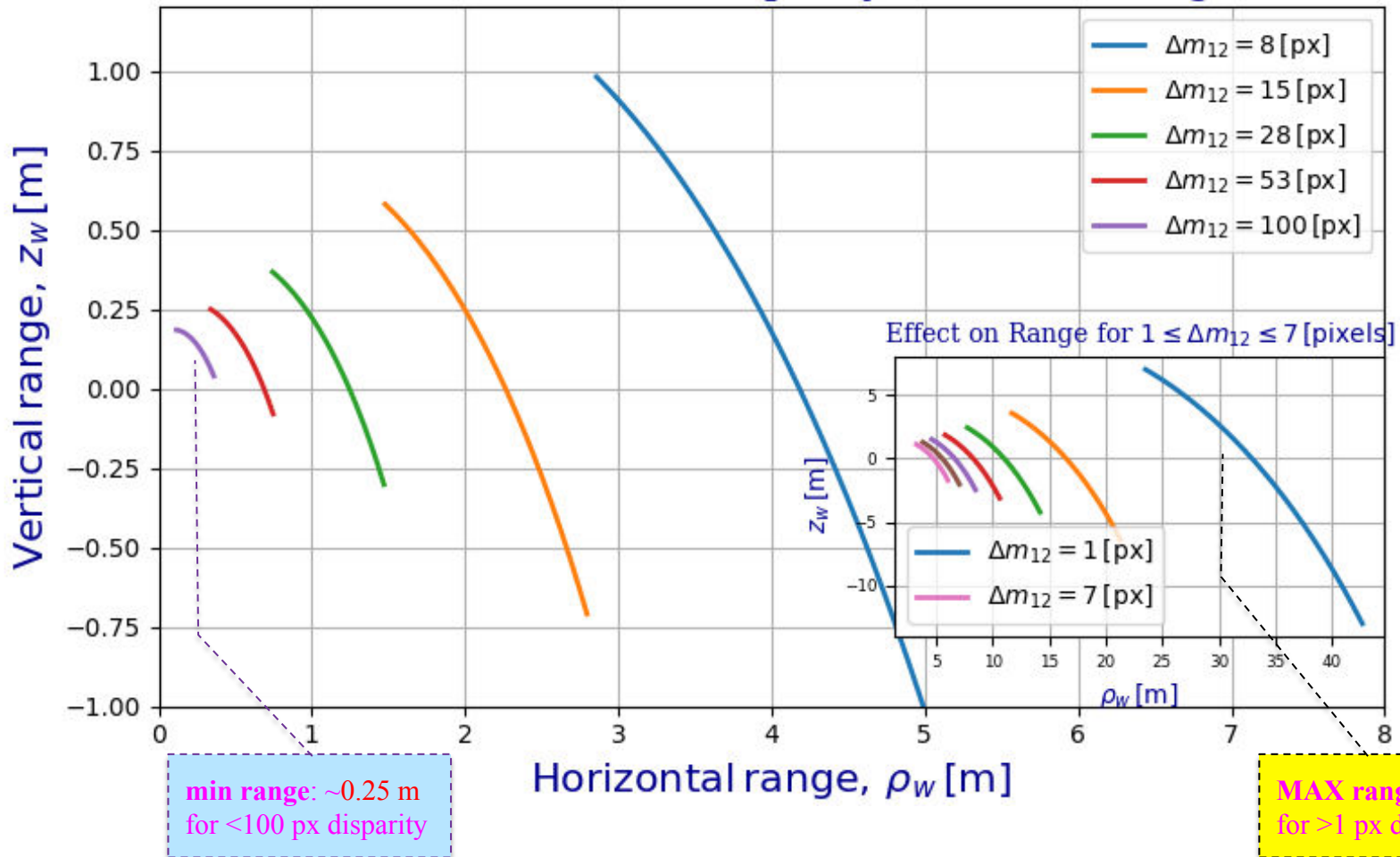
based on SROI near vertices



Hyperbolic SOS: Range Limits

<Intro> <**SOS**> <GUMS> <VO>

Effect of Omnistereo Pixel Disparity (Δm_{12}) on Range (ρ_w, z_w)



NOTE: using “far-sighted” rig



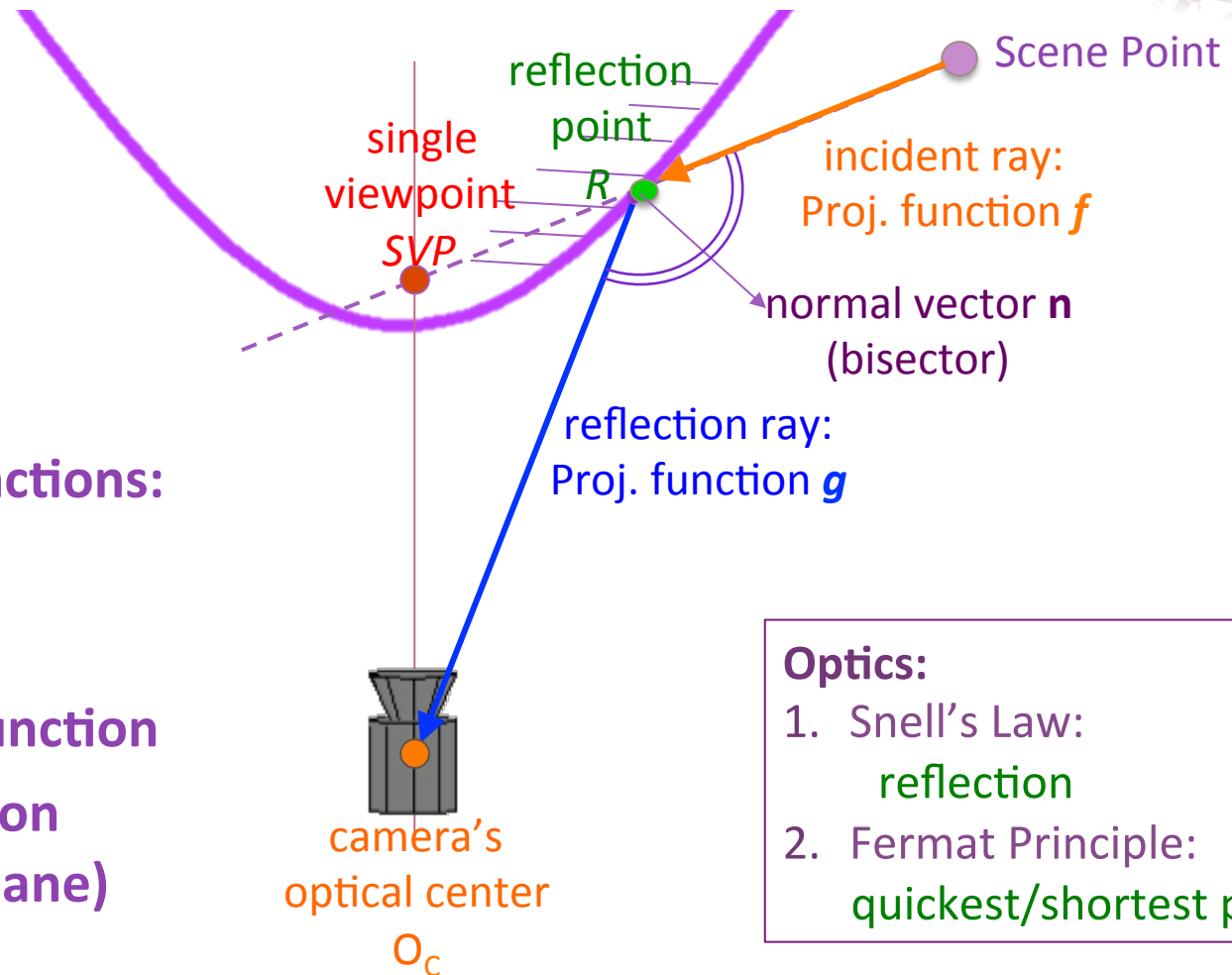
GUMS: A GENERALIZED UNIFIED MODEL FOR SOS

Peer-reviewed publication:

Carlos Jaramillo, Roberto G Valenti, and Jizhong Xiao.

“GUMS: A Generalized Unified Model for Stereo Omnidirectional Vision (Demonstrated Via a Folded Catadioptric System).”

In IEEE International Conference on Intelligent Robots and Systems (IROS), 2016, 2528–33. Korea



Composition of 2 functions:

$$g \circ f$$

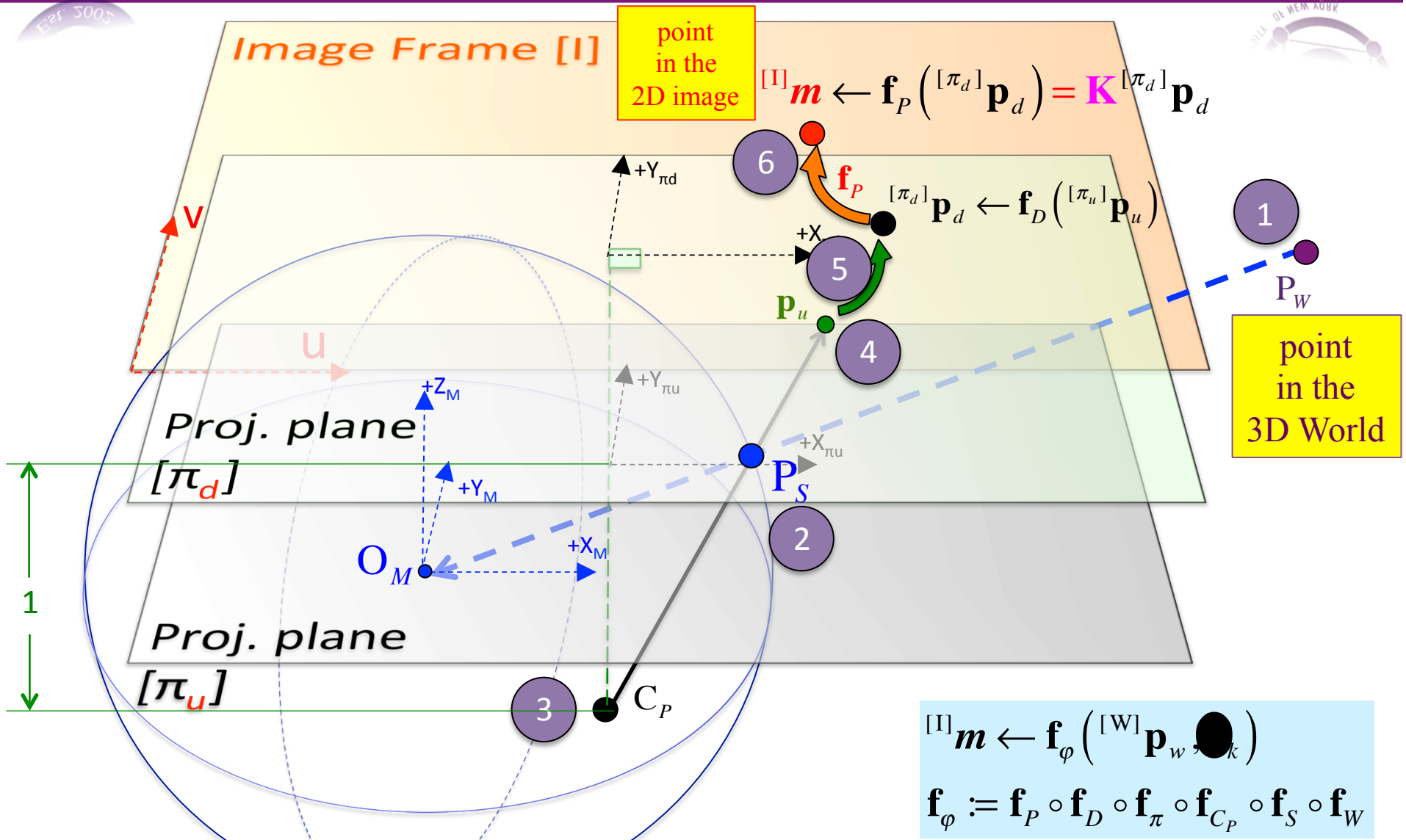
- f is a non-linear function
- g is a linear function (projection to a plane)

Optics:

1. Snell's Law: reflection
2. Fermat Principle: quickest/shortest path

Generalized Unified Model (GUM)

<Intro> <SOS> <GUMS> <VO>

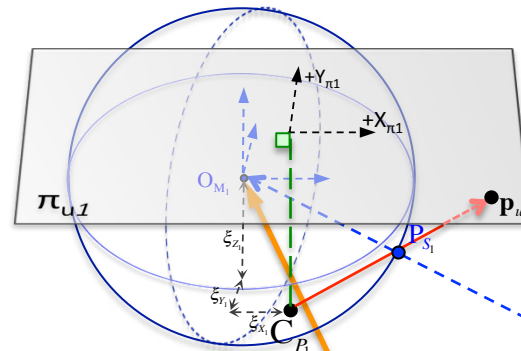
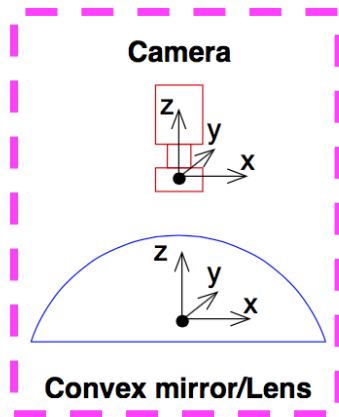


$${}^{[I]}m \leftarrow f_\varphi ({}^{[W]}p_w)$$

$$f_\varphi := f_p \circ f_D \circ f_\pi \circ f_{C_p} \circ f_S \circ f_W$$

GUMS in a general omnistereo configuration

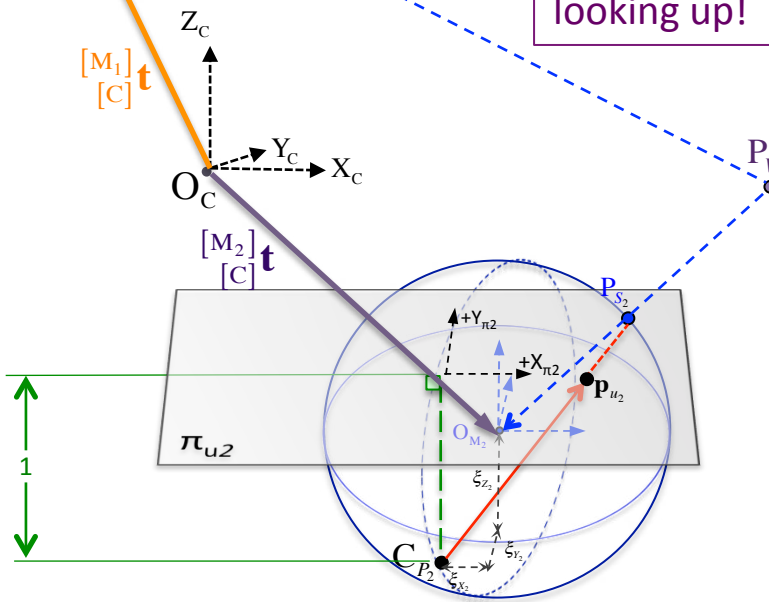
View 1



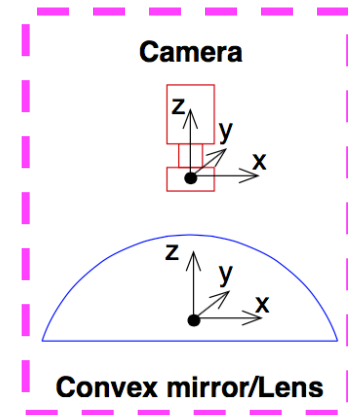
$$[M_1] \mathbf{p} = [M_1] \mathbf{t} + [C] \mathbf{p}$$

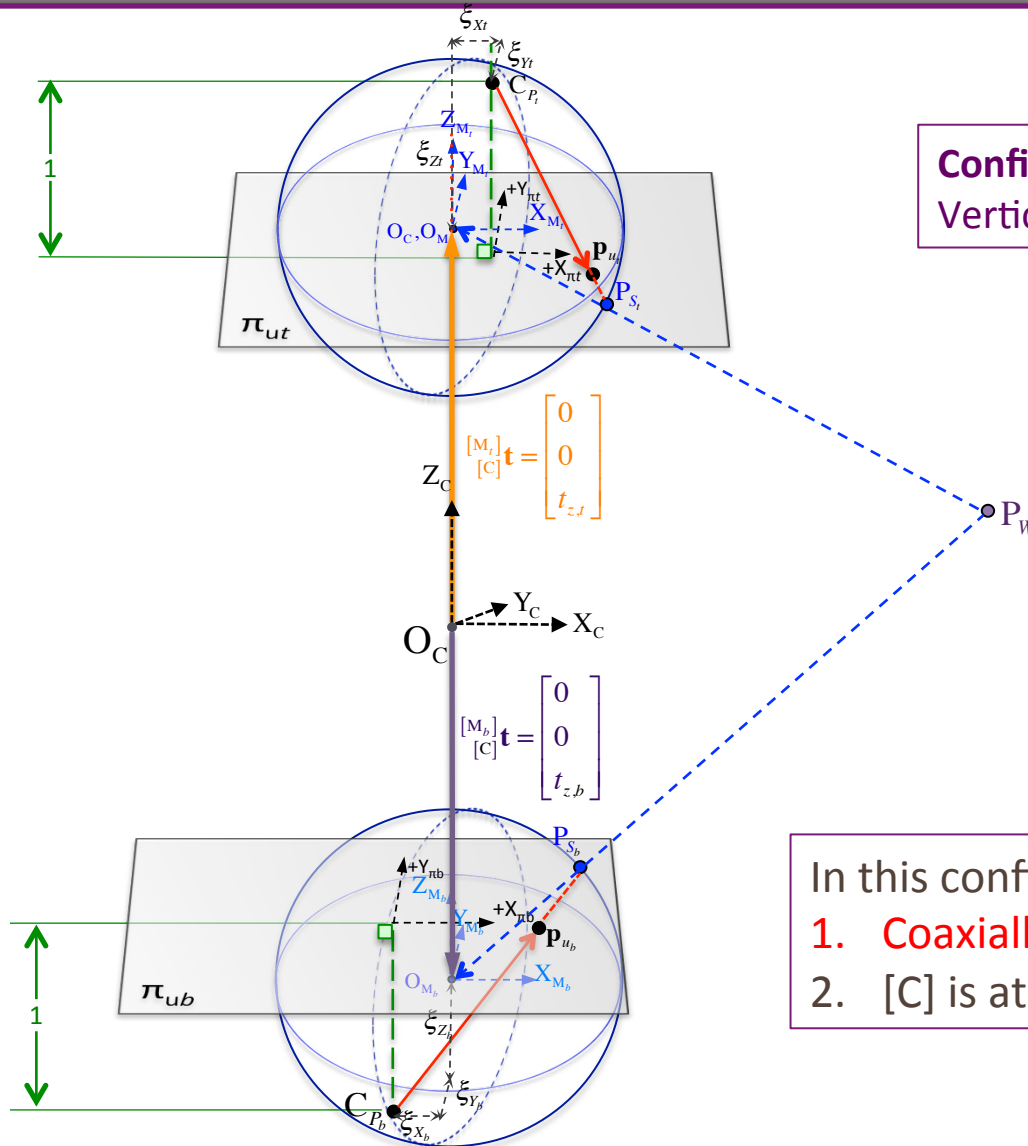
Configuration:
Two independent catadioptric ODVS
looking up!

$$[M_2] \mathbf{p} = [M_2] \mathbf{t} + [C] \mathbf{p}$$

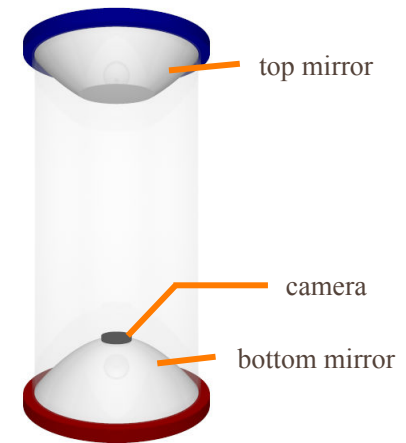


View 2





Configuration:
Vertical and "folded" omnistereo



In this configuration, **GUMS** is:

1. **Coaxially constrained**
2. $[C]$ is at coincident with $[M_t]$



GUMS Parameters

<Intro> <SOS> <**GUMS**> <VO>



For the coaxial-alignment constraint:

Extrinsic parameters:

$$\begin{bmatrix} [M_k] \\ [C] \end{bmatrix} \mathbf{t} = \begin{bmatrix} 0 \\ 0 \\ t_{z,k} \end{bmatrix}$$

$$\text{for } k = \{t, b\}$$

Intrinsic parameters:

$$\boldsymbol{\xi}_k = [\xi_X, \xi_Y, \xi_Z]_k;$$

$$\mathbf{d}_k = [d_1, d_2, d_3]_k;$$

$$\mathbf{c}_k = [\alpha, \gamma_1, \gamma_2, u_c, v_c]_k$$

generalized camera's
intrinsic parameters

We get:

$$\mathbf{x}_k = \begin{bmatrix} \boldsymbol{\xi}_k, & \mathbf{d}_k, & \mathbf{c}_k \end{bmatrix}_{(1 \times 11)}, \text{ for } k = \{t, b\}$$

This coaxial **GUMS** has 24 parameters:

$$\mathbf{GUMS} = \begin{bmatrix} t_{z,t}, & t_{z,b}, & \mathbf{x}_t, & \mathbf{x}_b \end{bmatrix}_{(1 \times 24)}$$

GUMS Parameters (Calibration)

<Intro> <SOS> <GUMS> <VO>

This coaxial **GUMS** has 24 parameters:

$$\mathbf{GUMS} = \begin{bmatrix} t_{z,t}, & t_{z,b}, & \mathbf{x}_t, & \mathbf{x}_b \end{bmatrix}_{(1 \times 24)}$$

We add the “extrinsic” transformations of the L planar grids wrt to $[C]$.

$$\begin{bmatrix} [C] \\ [G_g] \end{bmatrix} \mathbf{T} = \begin{bmatrix} [C] \mathbf{R}, & [C] \mathbf{t} \\ [G_g] \mathbf{R}, & [G_g] \mathbf{t} \end{bmatrix}, \forall g \in \{1, \dots, L\}$$

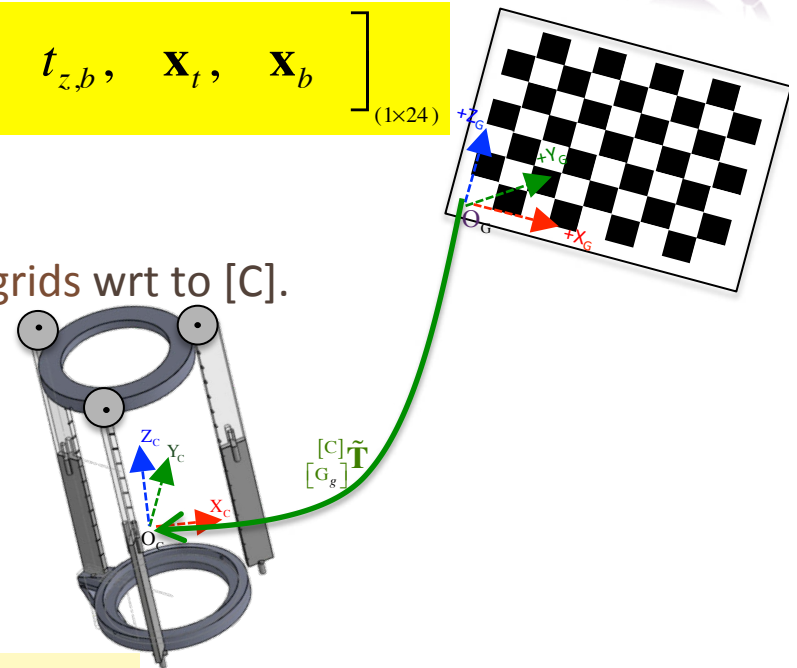
Using rotation quaternions:

$$\mathbf{g}_g = \begin{bmatrix} [C] \mathbf{q}, & [C] \mathbf{t} \\ [G_g] \mathbf{q}, & [G_g] \mathbf{t} \end{bmatrix} = \begin{bmatrix} [C] \\ [G_g] \end{bmatrix} \begin{bmatrix} \hat{q}_0, \hat{q}_1, \hat{q}_2, \hat{q}_3, t_x, t_y, t_z \end{bmatrix}$$

quaternions of form: $\mathbf{q} := \begin{bmatrix} q_0, & (q_1, q_2, q_3) \end{bmatrix}$
also represented by: $\mathbf{q} := q_0 + q_1 \hat{i} + q_2 \hat{j} + q_3 \hat{k}$

This **GUMS** has $24+7L$ parameters for **calibration**:

$$\mathbf{v}_{tb} = \begin{bmatrix} \{\mathbf{g}_1, \mathbf{g}_2, \dots, \mathbf{g}_L\}, & t_{z,t}, & t_{z,b}, & \mathbf{x}_t, & \mathbf{x}_b \end{bmatrix}_{(1 \times (24+7L))}$$





Calibration: Explained for GUMS



<Intro> <SOS> <GUMS> <VO>

Goal: To estimate a vector of parameters $\mathbf{v}_{tb} = \left[\{\mathbf{g}_1, \mathbf{g}_2, \dots, \mathbf{g}_L\}, t_{z,t}, t_{z,b}, \mathbf{x}_t, \mathbf{x}_b \right]_{(1 \times (24+7L))}$ such that it minimizes an **objective function** J that accumulates the *squared reprojection error*

NOTE: For L grid patterns of N points, **now** we have $4 \times N \times L$ points on the image.

$$\mathbf{v}_{tb}^* = \arg \min_{\mathbf{v}_{tb}} (J), \text{ where } J(\mathbf{v}) := \frac{1}{2} \sum_{k=[t,b]} \sum_{g=1}^L \sum_{i=1}^N f_m(\tilde{\mathbf{m}}_{ikg}, \mathbf{m}_{ikg})^2$$

$$\tilde{\mathbf{m}}_{ikg} \leftarrow \mathbf{f}_{\varphi_k} \left([{}^C] \tilde{\mathbf{p}}_{ig}, \bullet_k \right),$$

where $[{}^C] \tilde{\mathbf{p}}_{ig} \leftarrow \mathbf{f}_g \left([{}^{G_g}] \mathbf{p}_i, \tilde{\mathbf{g}}_g \right)$

$$\text{where } f_m(\tilde{\mathbf{m}}_{ikg}, \mathbf{m}_{ikg}) := \sqrt{(\tilde{u}_{ikg} - u_{ikg})^2 + (\tilde{v}_{ikg} - v_{ikg})^2}$$

\mathbf{m}_{ikg} is the **true** image position of corner point i in its pattern view g (from corner detection)

\mathbf{f}_{φ_k} is the projection function to estimate $\tilde{\mathbf{m}}_{ikg}$ image coordinates via GUM k corresponding to point $[{}^W] \mathbf{p}_{ig}$ from grid pattern g using $\bullet_k = \left[\begin{matrix} \tilde{t}_{z,k} & \tilde{\mathbf{x}}_k \end{matrix} \right]_{(1 \times 12)}$ parameters

Recall the projection function:

$$[{}^I_k] \mathbf{m}_{ig} \leftarrow \mathbf{f}_{\varphi_k} \left([{}^W] \mathbf{p}_i, \bullet_k \right) := \mathbf{f}_P \circ \mathbf{f}_D \circ \underbrace{\mathbf{f}_\pi \circ \mathbf{f}_{C_P} \circ \mathbf{f}_S}_{\mathbf{f}_H} \circ \mathbf{f}_W \circ \mathbf{f}_M \circ \mathbf{f}_G$$

misaligned synthetic case

Projection Error

Cyan: top mirror bounds

Mag: bottom mirror bounds

Centers:

• initial

+ calibrated

Blue: true detected points (m)

Green: ground-truth pose

RMSE = 2.24 [pixels]

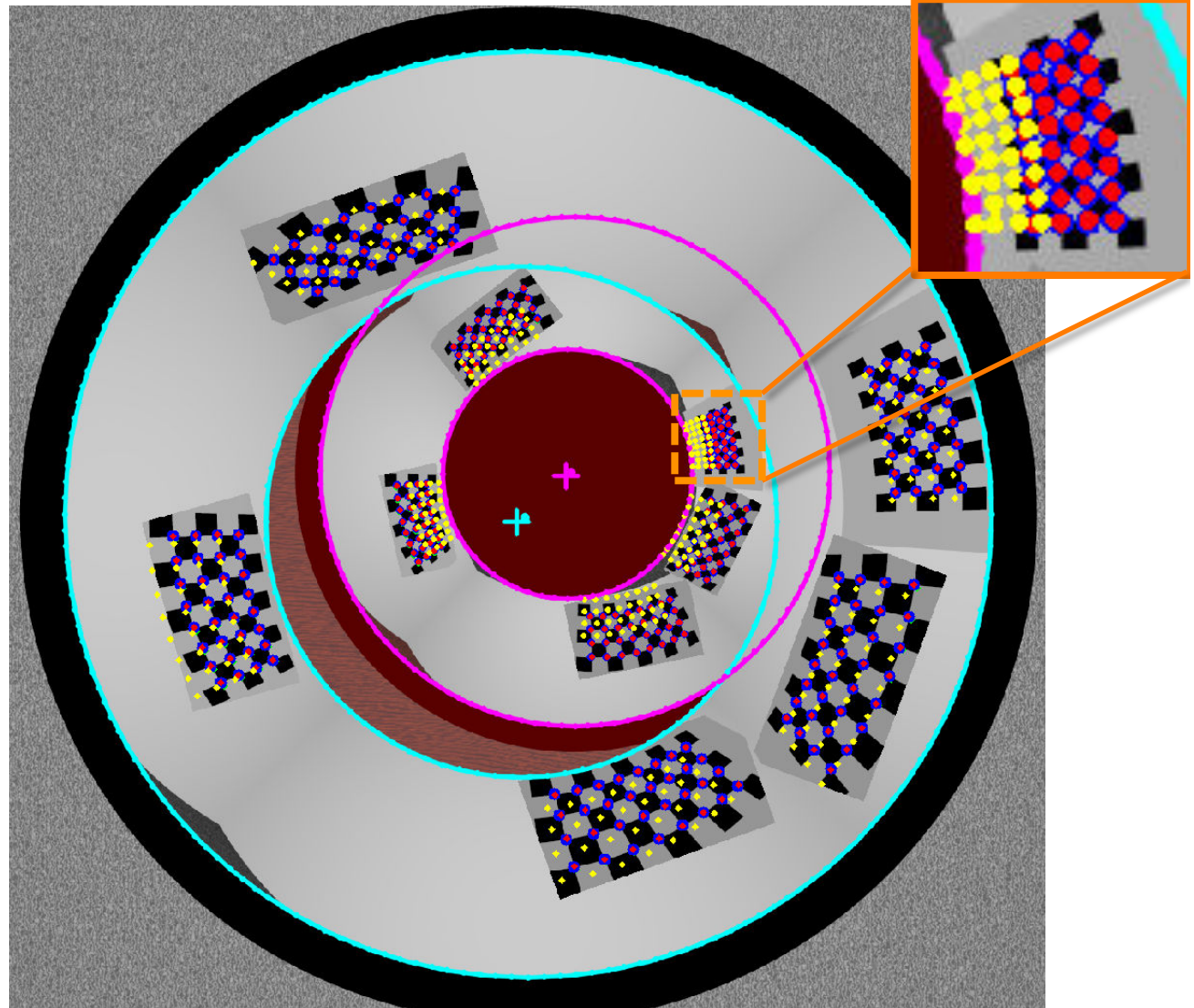
Red: estimated pose

RMSE = 0.39 [pixels]

Yellow: initial pose

RMSE = 21.42 [pixels]

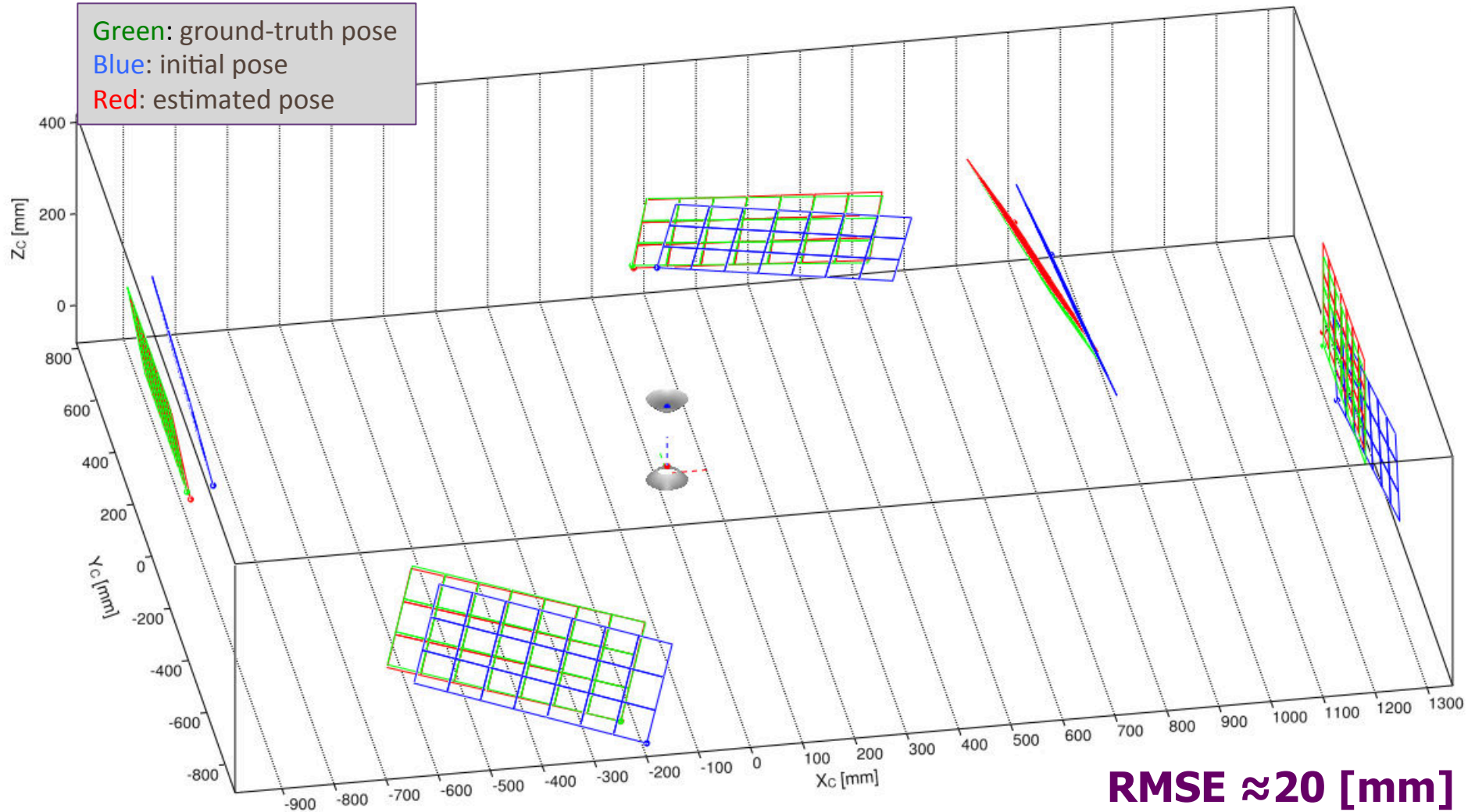
\tilde{m}



Results from a Misaligned SOS

<Intro> <SOS> <**GUMS**> <VO>

Estimated grid poses: **misaligned** synthetic SOS



<Intro> <SOS> <**GUMS**> <VO>

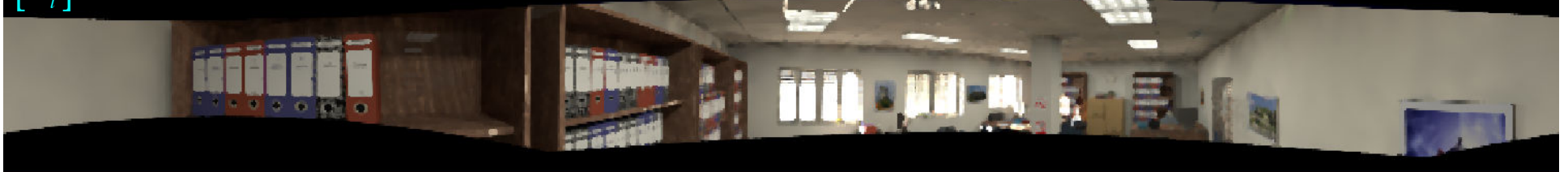
$[\Xi]_{\Delta m_{tb}}$

Depth Map Image (using Semi-Global Block Matching)



$[\Xi]_t$

Reference Panorama (provides higher view via Top Mirror)



$[\Xi]_b$

Target Panorama (provides lower view via Bottom Mirror)



circular
bottom view
(masked)



$$[\Xi_b] m_b = \begin{bmatrix} u_t \\ v_t + \Xi_{\Delta m_{tb}} \end{bmatrix} \Big|_{[\Xi_t] m_t}$$

from **misaligned** synthetic experiment

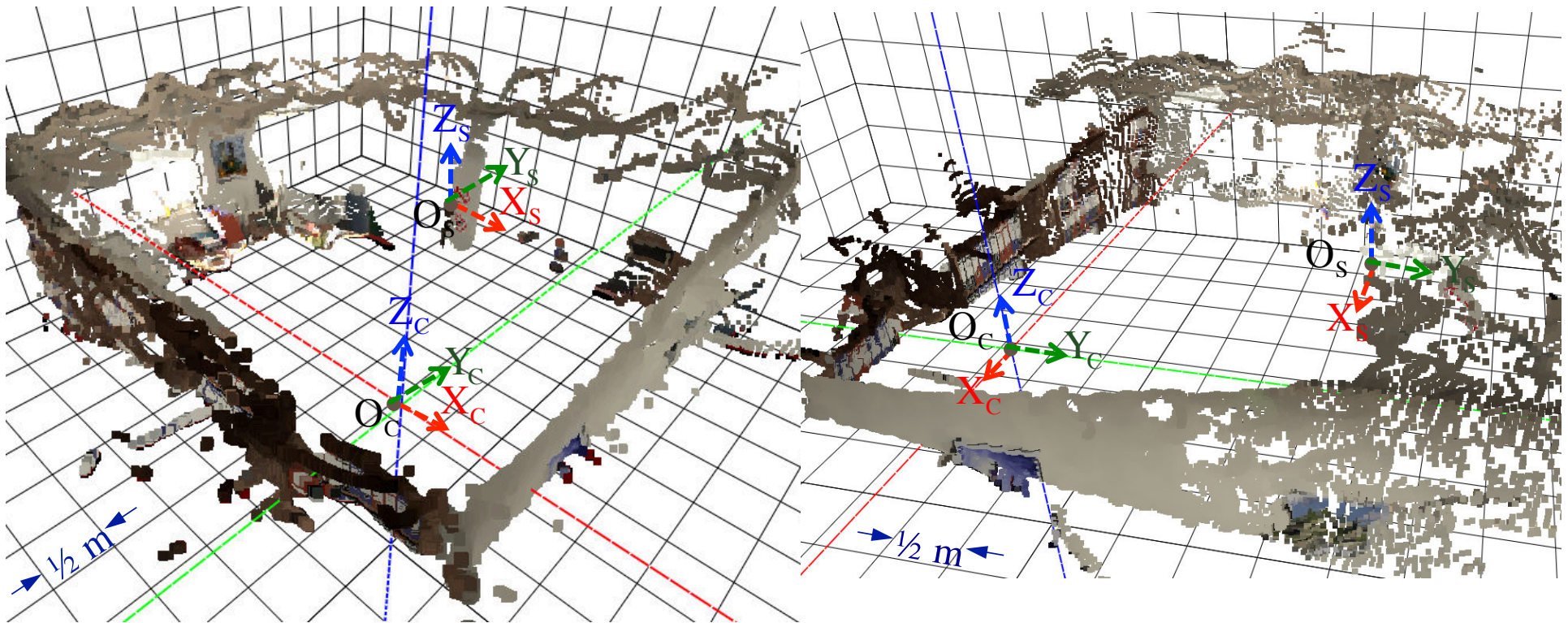
circular
top view
(masked)



3D Views

with **Perfect Alignment**

with **Misalignments**



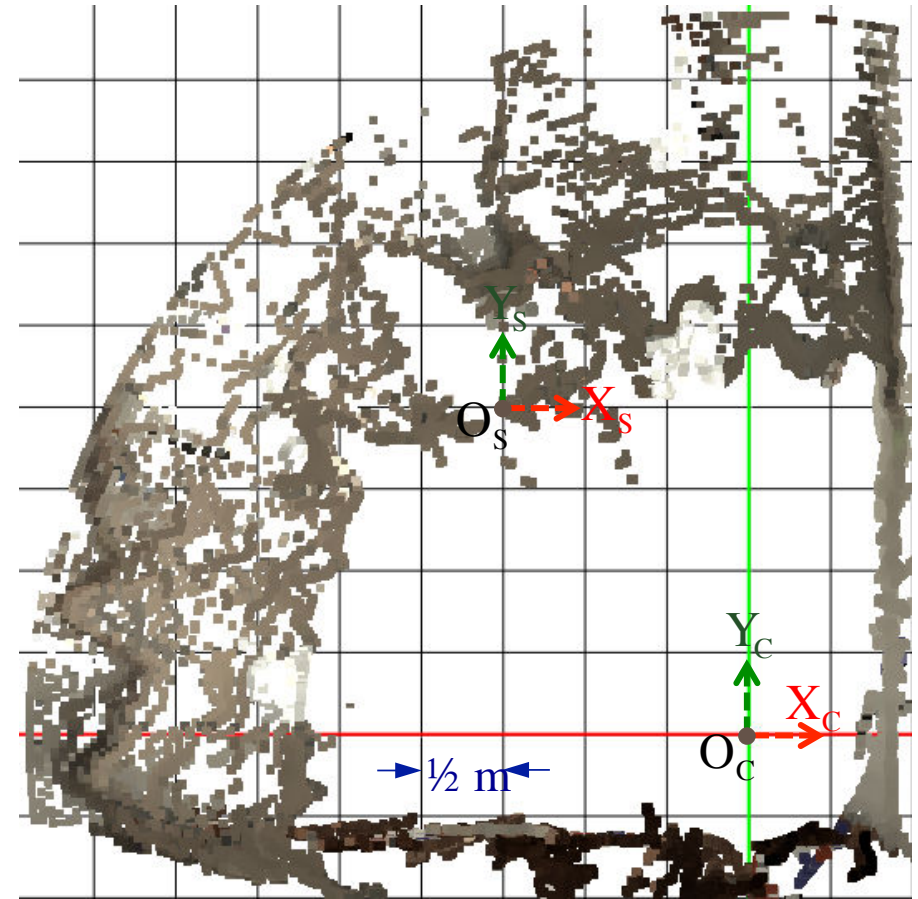
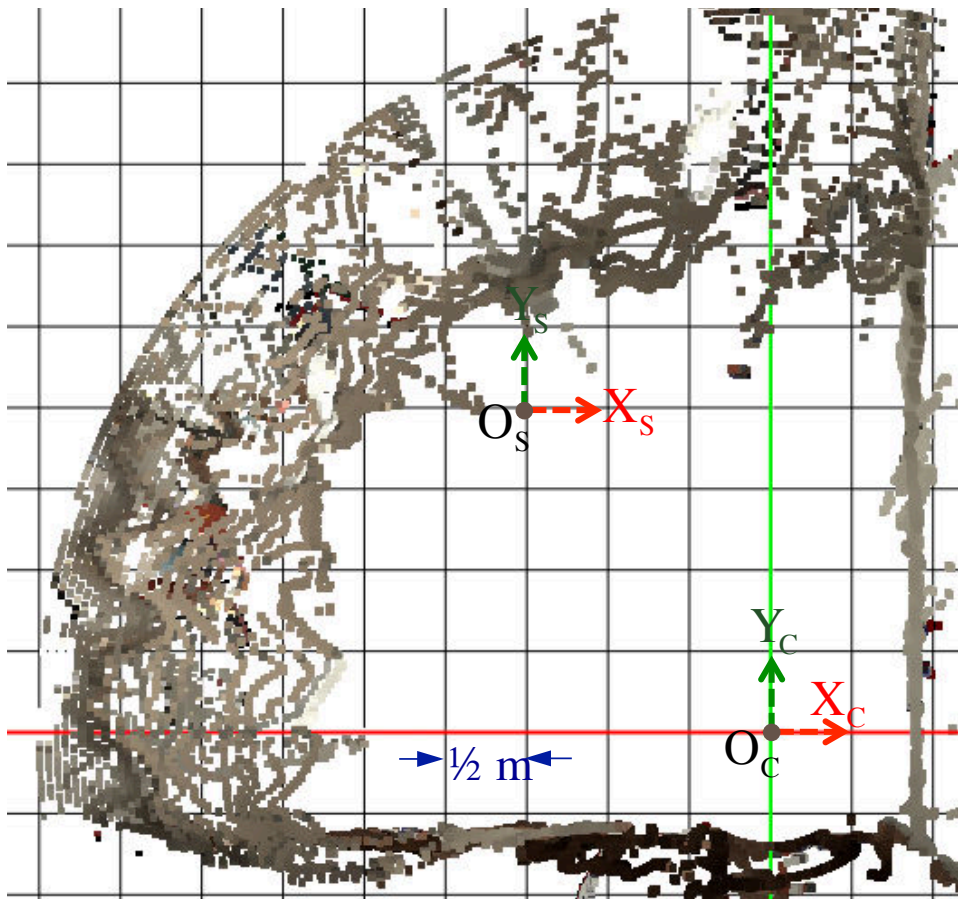
NOTE: The screenshot is taken from different viewpoints

from **synthetic** experiments

Orthographic Views

with **Perfect Alignment**

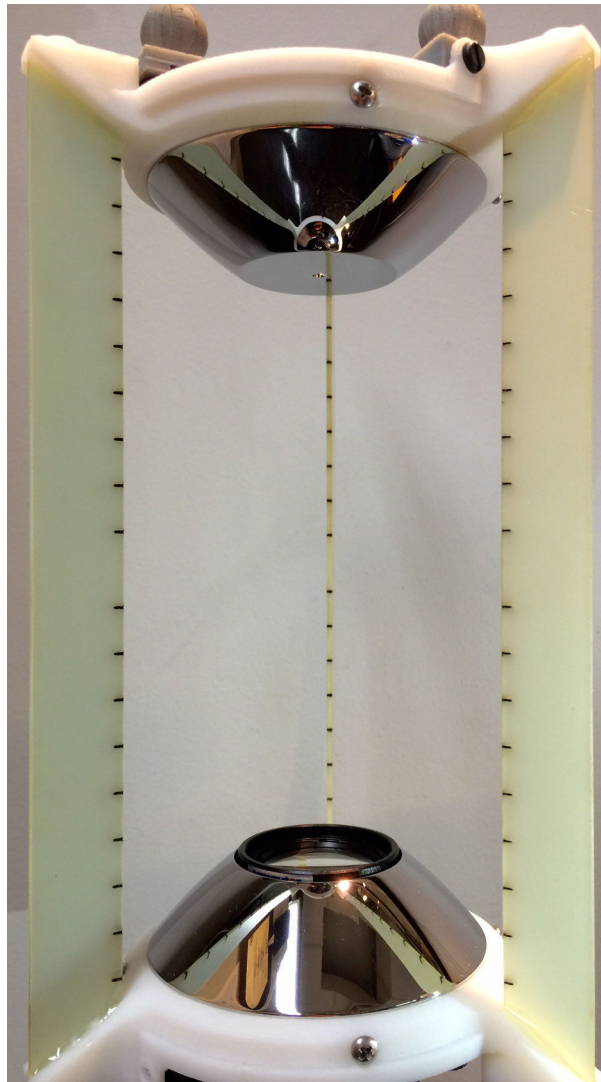
with **Misalignments**



from synthetic experiments

Real-Life Calibration Experiments

<Intro> <SOS> <**GUMS**> <VO>





Calibration Approach Comparison

<Intro> <SOS> <**GUMS**> <VO>



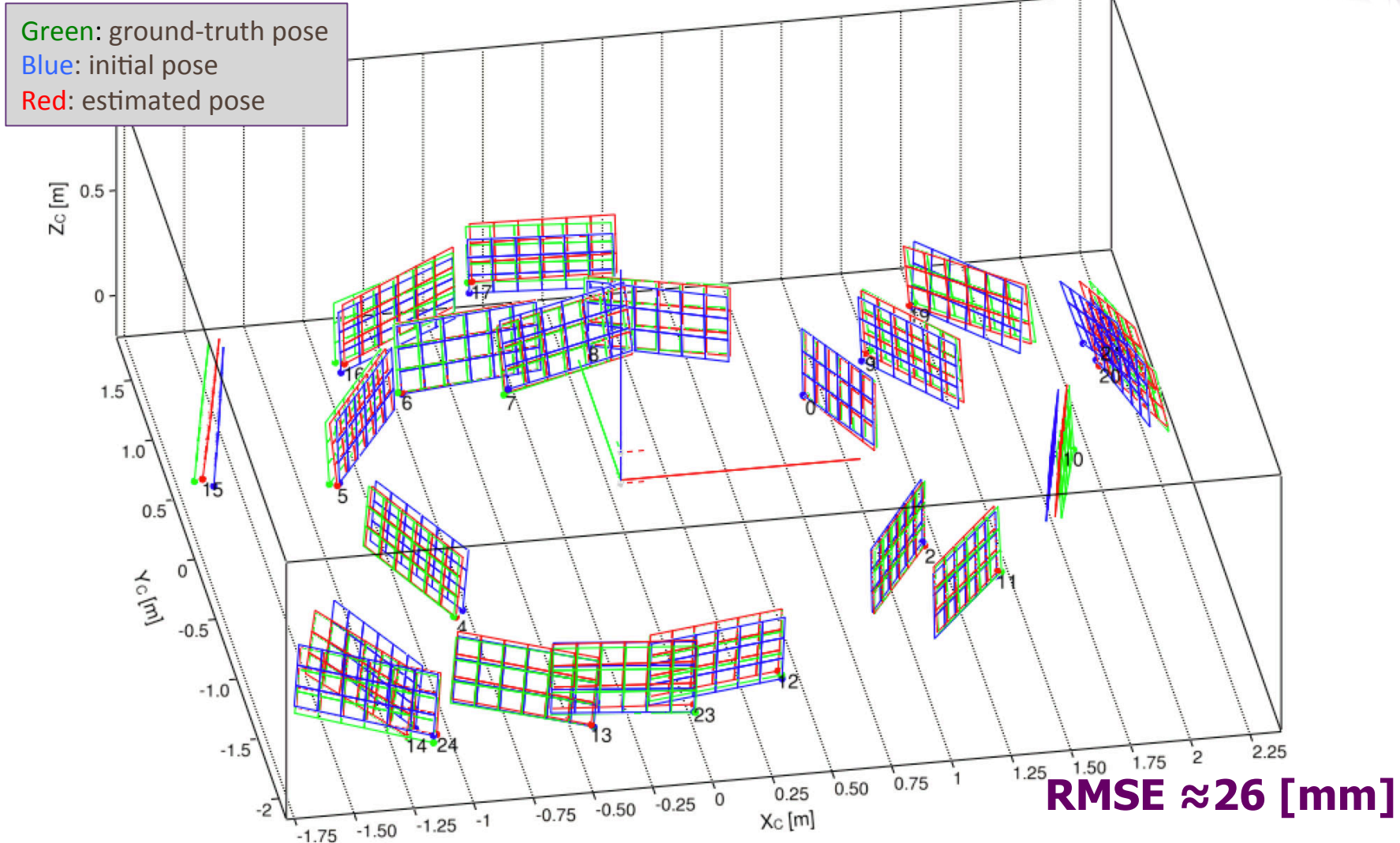
RMSE for **Real-Life** Calibration Experiments

Sight	Coupled	2D Error [px]		3D Error from GT [mm]	
		GT	no GT	Triang.	[G] Pose
Near	Yes	4.86	2.56	6.06	3.66
	No	11.02	10.94	22.34	4.64
Far	Yes	3.71	1.64	126.81	26.38
	No	5.65	3.27	267.69	45.38

GUMS **coupled** approach **reduces** the overall error

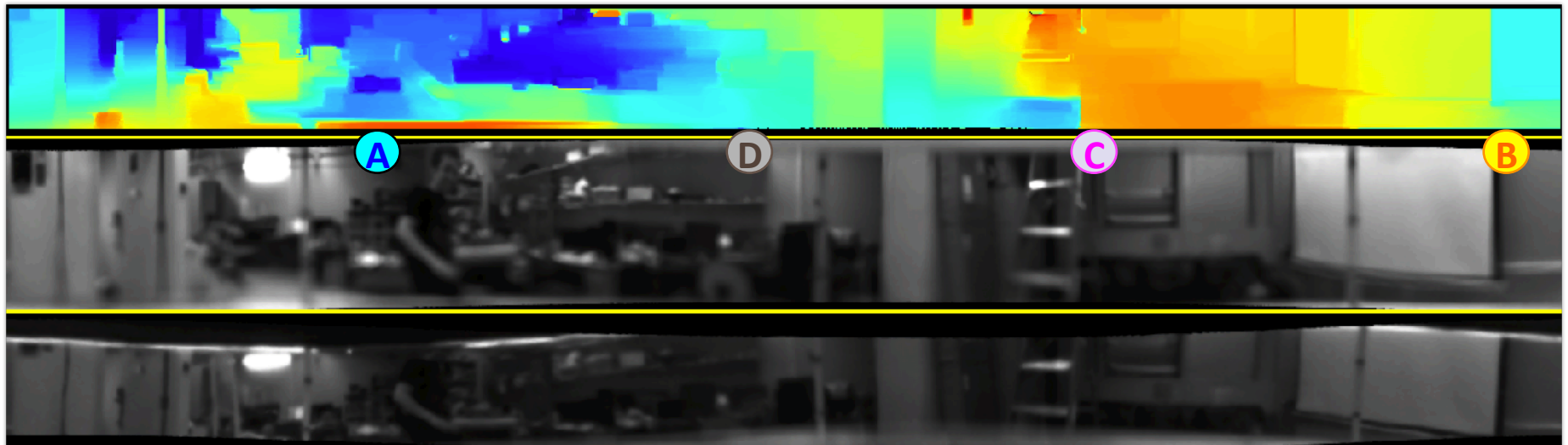
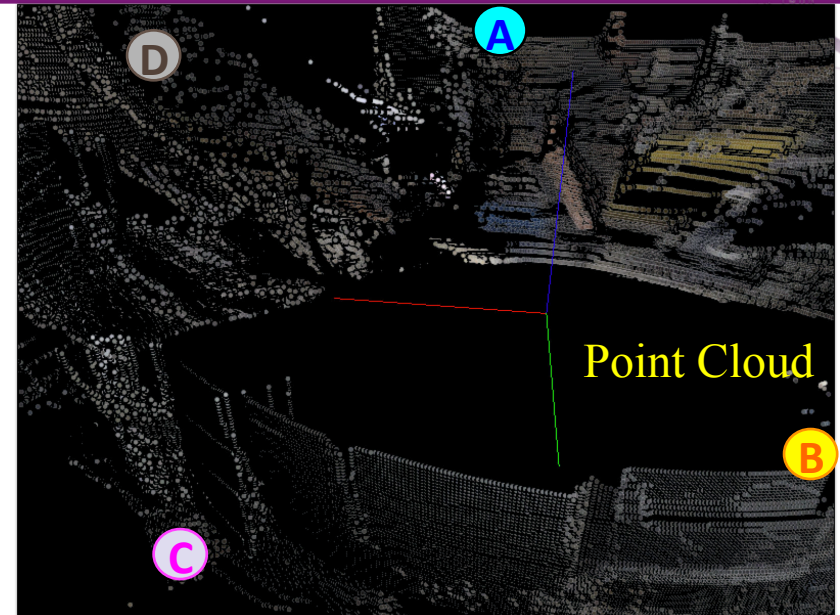
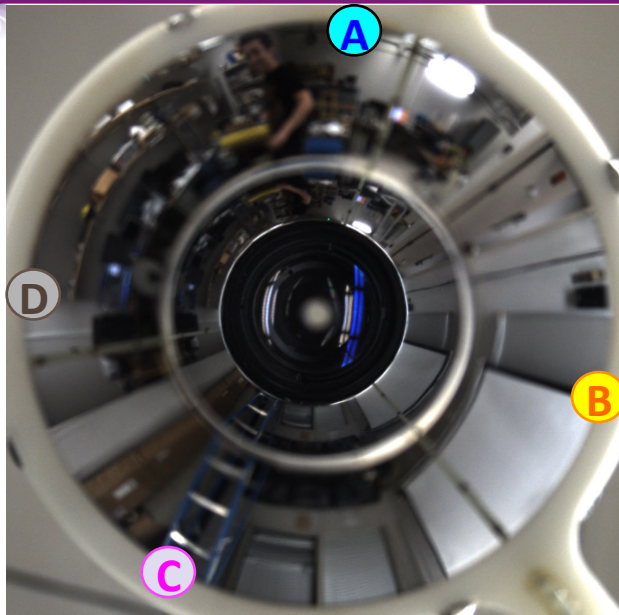
Newest
hyperbolic
single-camera SOS

Estimated grid poses: far-sighted real-life SOS



Real-Life Calibrated Example

<Intro> <SOS> <**GUMS**> <VO>





VISUAL ODOMETRY WITH A SINGLE-CAMERA SOS

Publication under review:

Carlos Jaramillo, Liang Yang, J. Pablo Muñoz, Yuichi Taguchi, and Jizhong Xiao.
“*Visual Odometry with a Single-Camera Stereo Omnidirectional System.*”
In IEEE Robotics and Automation Letters. Received in May 2018

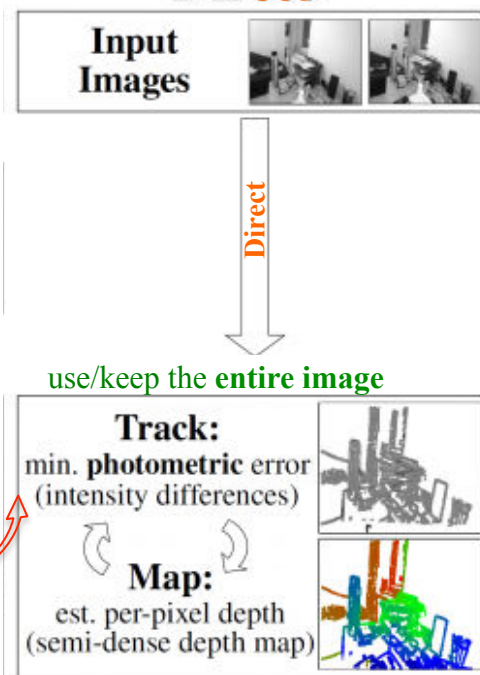
Visual Odometry in General

<Intro> <SOS> <GUMS> <VO>

VO Definition: Estimation of the 3D pose of a vision sensor's frame wrt a reference frame

- **The reference frame:**
 - A current tracking keyframe chosen heuristically based on some criteria
 - The world or map frame (absolute pose)
- **Tracking methods:**

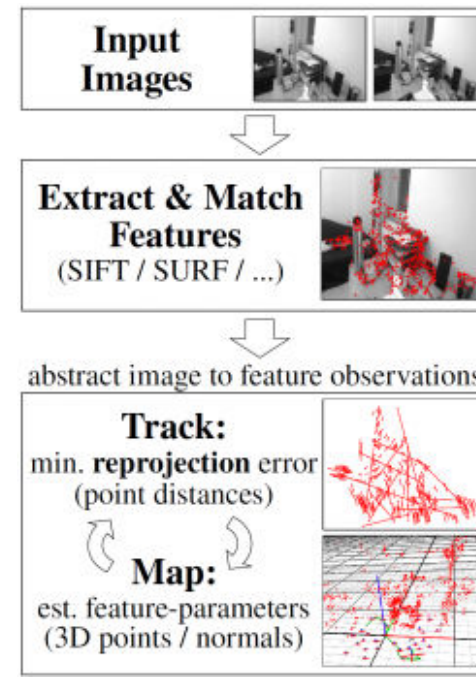
Direct



As done for: LSD-SLAM, DSO, & **DMT**

VS.

Feature-based



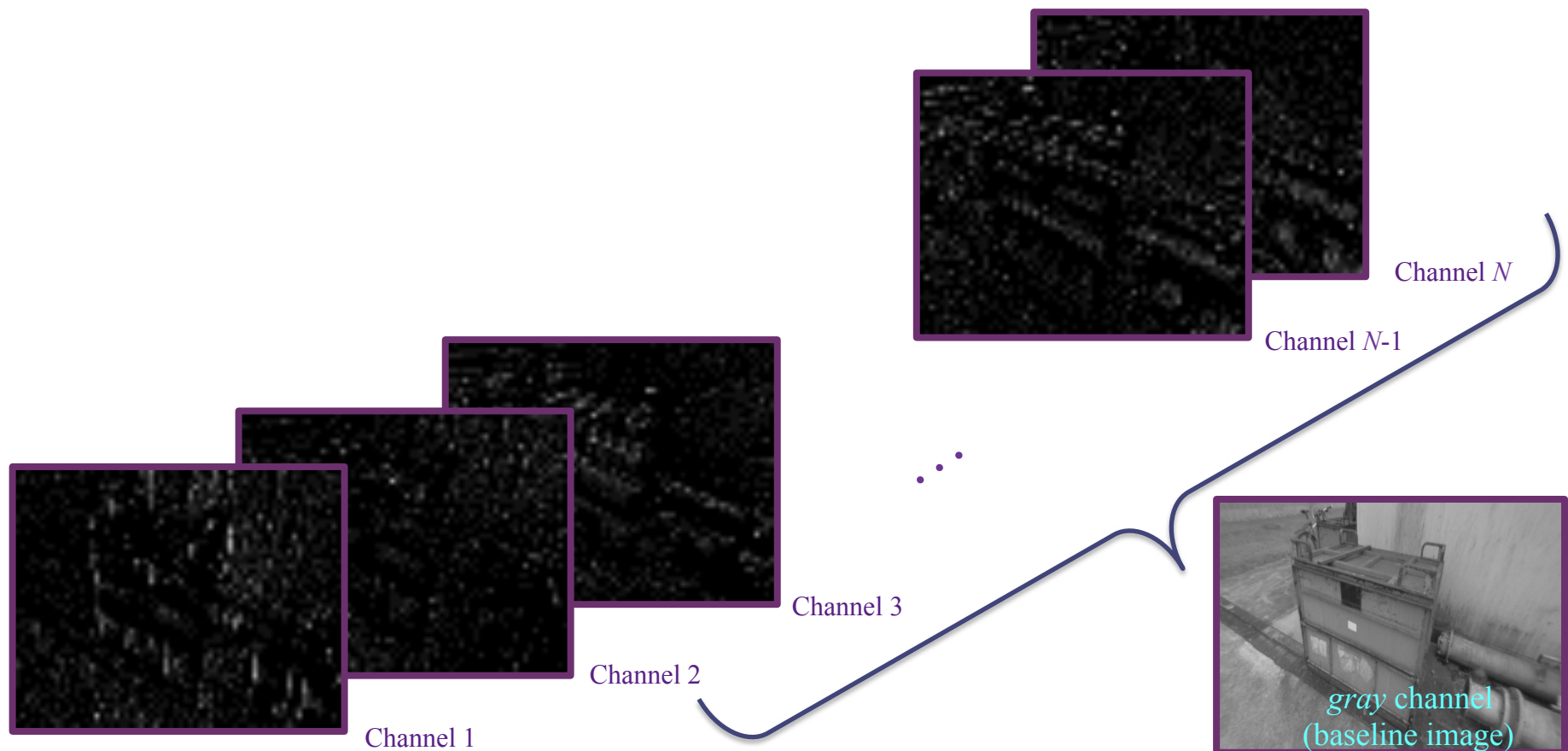
As done for: PTAM, ORB SLAM, etc.

Lucas-Kanade algorithm:
brightness constraint

$$\mathbf{x}' = \mathbf{w}(\mathbf{x}; \xi)$$

- **Direct Approach** (*not presented here*):

Direct Tracking of Multi-dimensional Features





Feature-Based VO with SOS



<Intro> <SOS> <GUMS> <VO>

- **Frame-to-Frame Visual Odometry framework**
 - **Goal:** solve for the relative SE3 pose ${}^{[K]}_{[C_t]}\tilde{\mathbf{T}}$ between frames
 - **Feature-based** approach:
 - Keypoints detected via “*Good Features to Track*”
 - Keypoints described as Oriented Robust Binary (*ORB*) features
 - Frame $[C_t]$ was tracked with respect to its reference keyframe $[K]$
 - Keyframe creation:
 - If tracking correspondences are at least 10% of the current average:
 - Due to change in translation: $\Delta \mathbf{t}_{C_t \rightarrow K} > 1$ [cm]
 - Due to change in rotation angle: $\theta_{\Delta \mathbf{R}_{C_t \rightarrow K}} > 1^\circ$
 - Using Kneip’s **NP3P** algorithm in a RANSAC fashion:
 - 3D-to-2D feature point registration approach from 3 points
 - Using a non-central model for bearing angle projection minimization
 - Final RANSAC pose model ${}^{[K]}_{[C_t]}\tilde{\mathbf{T}}^{(s_r)}$ is refined further via Levenberg-Marquardt

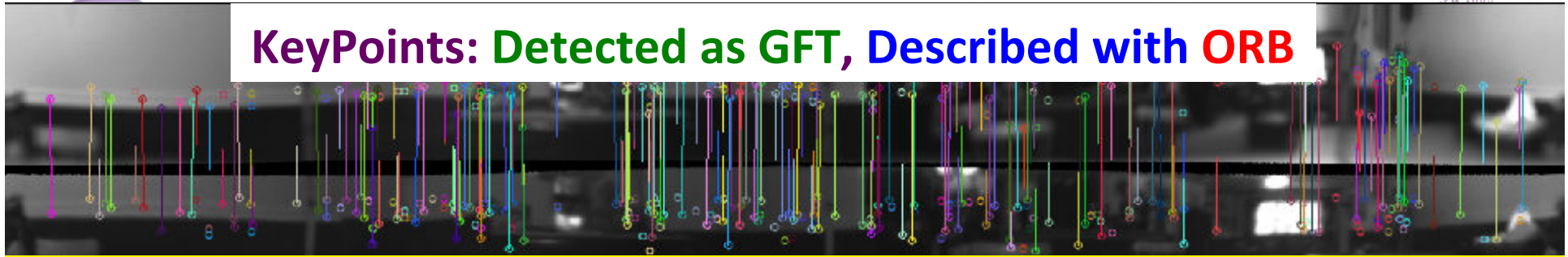


Tracking Features (Static Stereo)

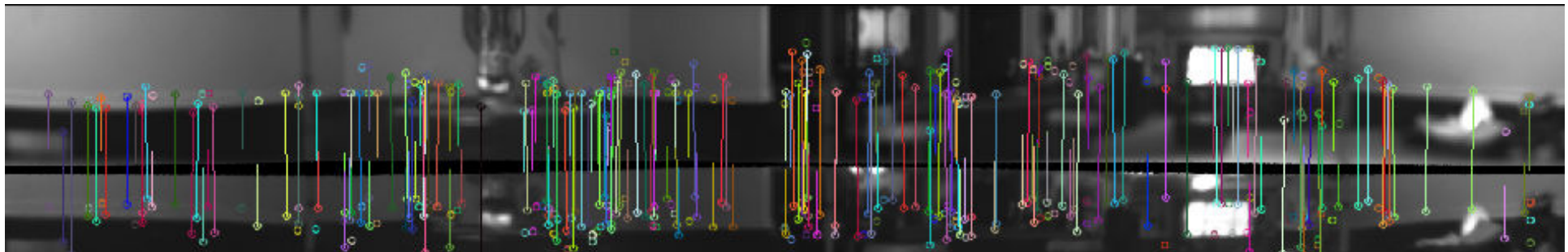


<Intro> <SOS> <GUMS> <VO>

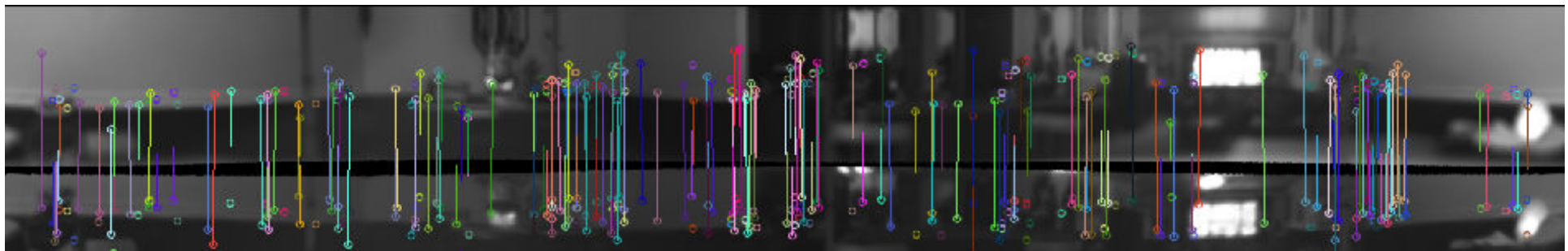
KeyPoints: Detected as GFT, Described with ORB



$$M_{top2bot}^{(K)} := \left\{ [E_K] (\mathbf{m}_{top}, \mathbf{m}_{bot})_i \text{ matched point-pairs from static omnistereo for the reference frame } [K] \right\}$$

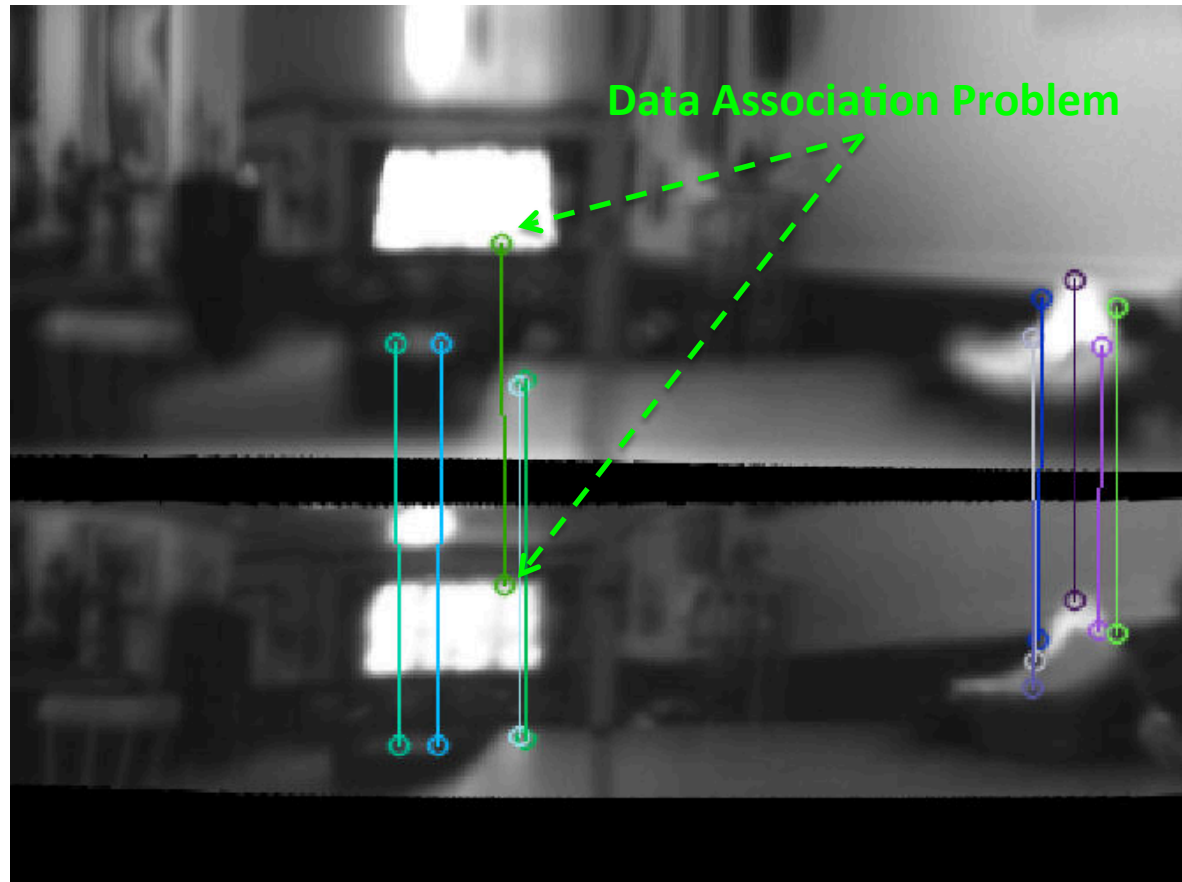


$$M_{top2bot}^{(C_t)} := \left\{ [E_{C_t}] (\mathbf{m}_{top}, \mathbf{m}_{bot})_i \text{ matched point-pairs from static omnistereo for tracking frame } [C_t] \right\}$$



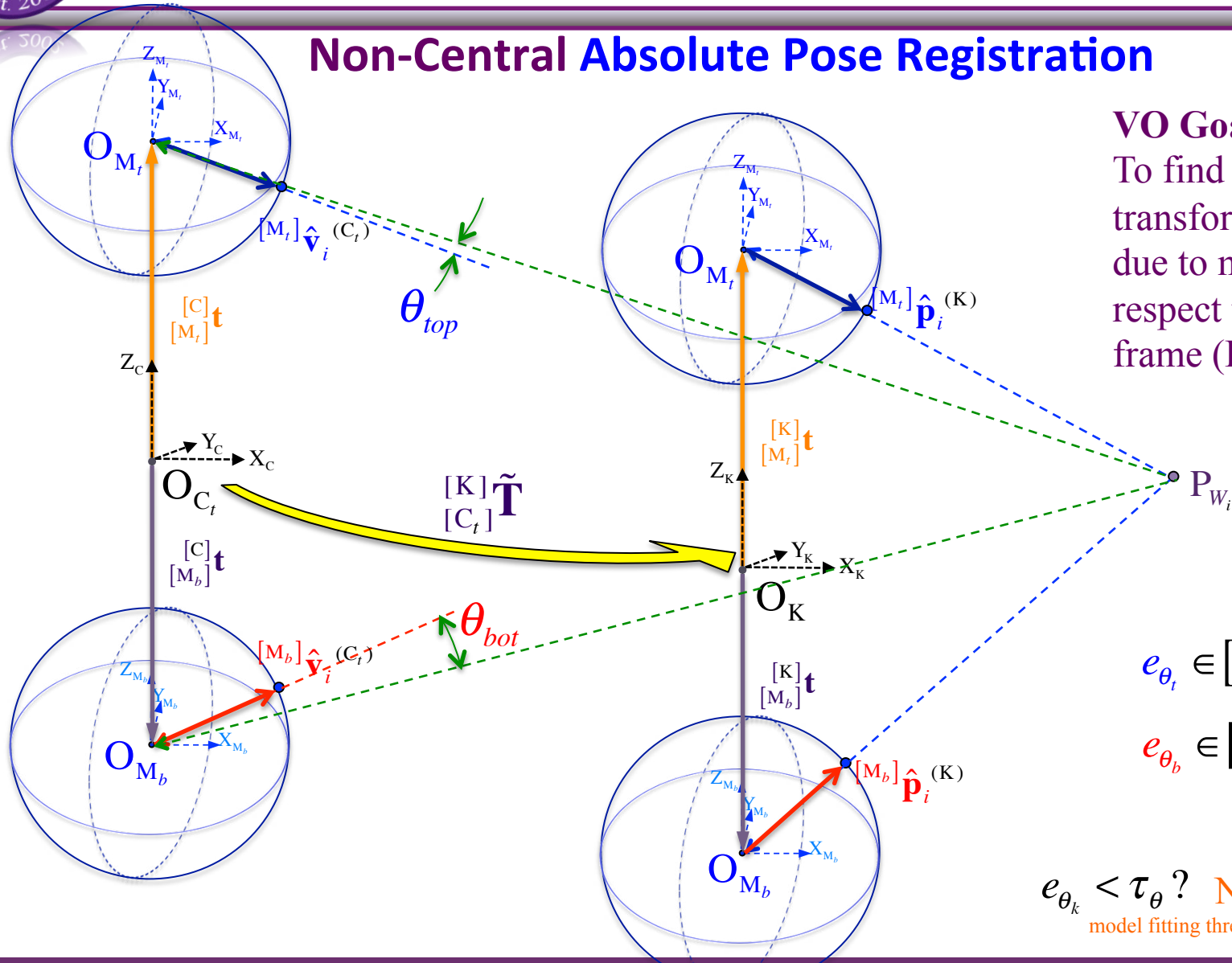
$$M_{top2bot}^{(C_{t+1})} := \left\{ [E_{C_{t+1}}] (\mathbf{m}_{top}, \mathbf{m}_{bot})_i \text{ matched point-pairs from static omnistereo for tracking frame } [C_{t+1}] \right\}$$

Erroneous point correspondences (**outliers**) must be removed



Example of some point correspondences among panoramas

Non-Central Absolute Pose Registration



VO Goal:
To find relative transform $\begin{bmatrix} [K] \\ [C_t] \end{bmatrix} T$ due to motion with respect to a *reference* frame (Keyframe K)

$$e_{\theta_t} \in [0, 2]$$

$$e_{\theta_b} \in [0, 2]$$

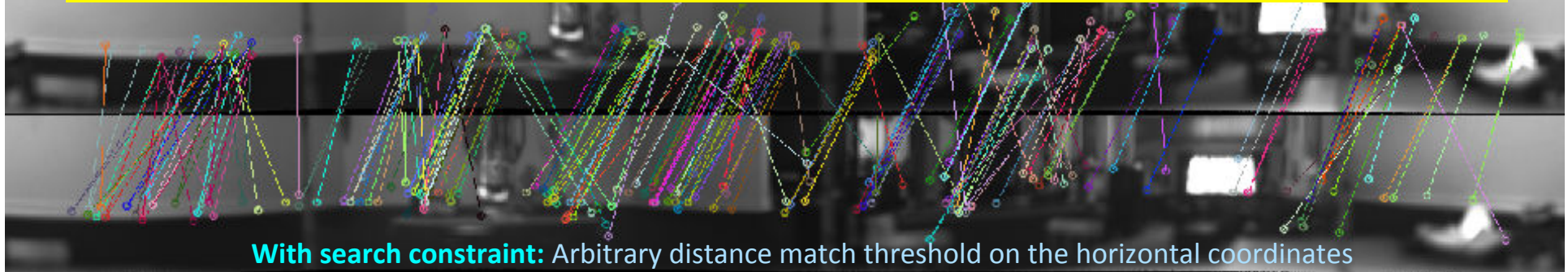
$e_{\theta_k} < \tau_{\theta}$? No \rightarrow outlier
model fitting threshold

Non-Central Absolute Pose Registration (among Top views)

Correspondences among moving frames

Initial set of 2D point correspondences at iteration s_0

$$M_{top2top}^{(C_t, s_0)} := \left\{ \left(\begin{matrix} [E_{C_t}] \\ m \end{matrix}, \begin{matrix} [E_K] \\ m \end{matrix} \right)_{top, i}^{(s_0)} \text{ initial point-pairs between frames } [C_t] \text{ and } [K] \text{ top views} \right\}$$



Final set of 2D point correspondences fitting the model $\begin{matrix} [C_{ref}] \\ [C_k] \end{matrix} T$ estimated via RANSAC at iter s_r

$$M_{top2top}^{(C_t, s_r)} := \left\{ \left(\begin{matrix} [E_{C_t}] \\ m \end{matrix}, \begin{matrix} [E_K] \\ m \end{matrix} \right)_{top, i}^{(s_r)} \text{ final point-pairs between frames } [C_t] \text{ and } [K] \text{ top views} \right\}$$

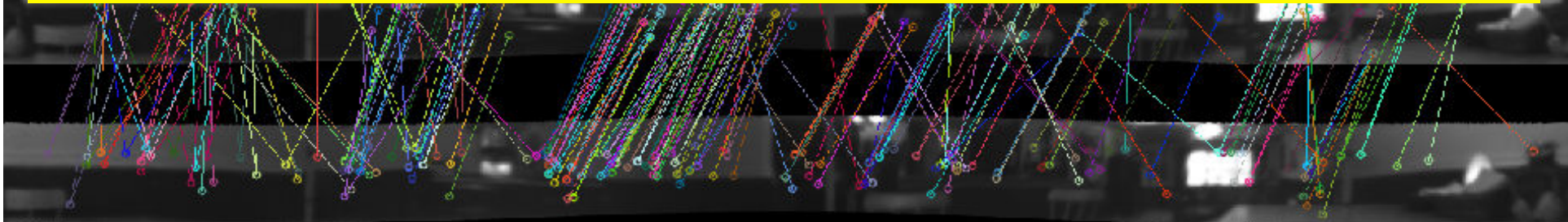


Non-Central Absolute Pose Registration (among Bottom views)

Correspondences among moving frames

Initial set of 2D point correspondences at iteration s_0

$$M_{bot2bot}^{(C_t, s_0)} := \left\{ \left({}^{[E_{C_t}]}m, {}^{[E_K]}m \right)_{bot,i}^{(s_0)} \text{ initial point-pairs between frames } [C_t] \text{ and } [K] \text{ bottom views} \right\}$$



With search constraint: Arbitrary distance match threshold on the horizontal coordinates:

Final set of 2D point correspondences fitting the model ${}_{[C_k]}^{[C_{ref}]}T$ estimated via RANSAC at iter s_r

$$M_{bot2bot}^{(C_t, s_r)} := \left\{ \left({}^{[E_{C_t}]}m, {}^{[E_K]}m \right)_{bot,i}^{(s_r)} \text{ final point-pairs between frames } [C_t] \text{ and } [K] \text{ bottom views} \right\}$$





Feature-Based VO: 3D-to-2D

<Intro> <SOS> <GUMS> <VO>



Non-Central Pose Registration

RANSAC phase

Joint set of 2D point correspondences fitting the model ${}_{[C_t]}^{[K]}T^{(s_j)}$ estimated via Non-Perspective-three-Point (NP3P) + RANSAC

$$M_{k2k}^{(t,s_j)} := \left\{ \left(\begin{matrix} [E_{C_t}] \mathbf{m}, [E_K] \mathbf{m} \end{matrix} \right)_{k,i}^{(s_j)} \mid e_{\theta_{kj}} \left(\begin{matrix} [K] T^{(s_j)} \\ [C_t] \end{matrix} \right) < \tau_{\theta}, k \in \{top, bot\}, i \in M_{ALL} \right\}$$

where j is the RANSAC iteration index

Optimization phase

Non-linear optimization using the final set of inliers $M_{k2k}^{(C_t, s_r)}$, and ${}_{[C_t]}^{[K]}T^{(s_r)}$ as the initial pose

$${}_{[C_t]}^{[K]}T^* = \arg \min_{{}_{[C_t]}^{[K]}T} (J), \text{ where } J({}_{[C_t]}^{[K]}T) := \frac{1}{2} \sum_{k=top, bot} \sum_{i=1}^{N_k} e_{\theta_{k,i}}$$

at the s_r final RANSAC iteration

Datasets and Evaluation

<Intro> <SOS> <GUMS> <VO>

Performance comparison against baseline 3D sensor (RGB-D camera)



RGB-D Camera

Single-camera SOS

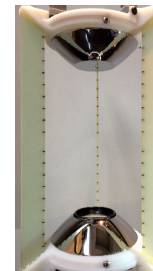
Synthetic

- Photo-realistic simulation
 - Raytraced with POV-Ray
- Have 4 **pose** sequences (paths) in the same “office” scene
- Simulated sensors
 - Omnistereo images
 - Associated RGB-D images



Real

- **Ground-truth** from *mocap* system
 - Indoors only
 - Small capture volume: 6x3x2 m
 - Went in/out of room-hallway (50m)
- Hardware:



- Hyperbolic rig (ready)

- Pointgrey **Blackfly** Specs:

- » Global Shutter at 30 FPS
- » 1920x1200 pixels

- Asus Xtion Pro Live



- » VGA resolution 640x480 pixels

[Datasets Link](#)

Synthetic Dataset

<Intro> <SOS> <GUMS> <VO>

$t = 0$

Office – Seq. # 0

$t = 500$



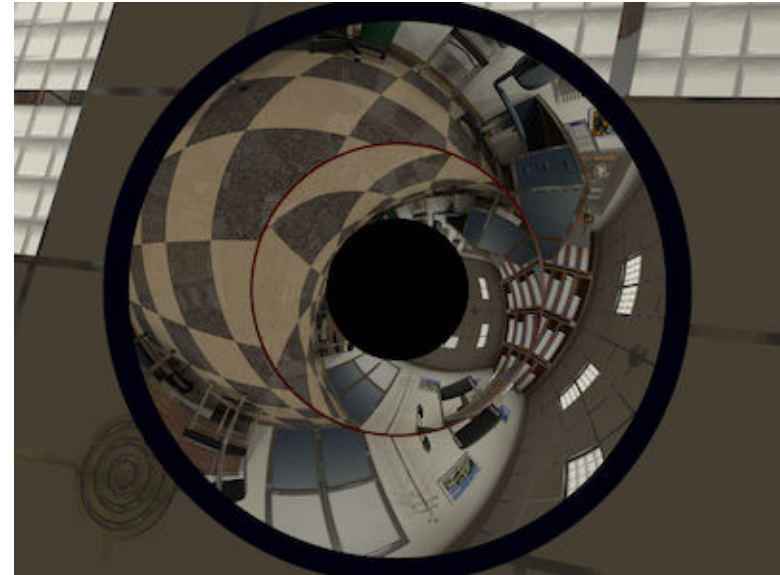
Synthetic Dataset

<Intro> <SOS> <GUMS> <VO>

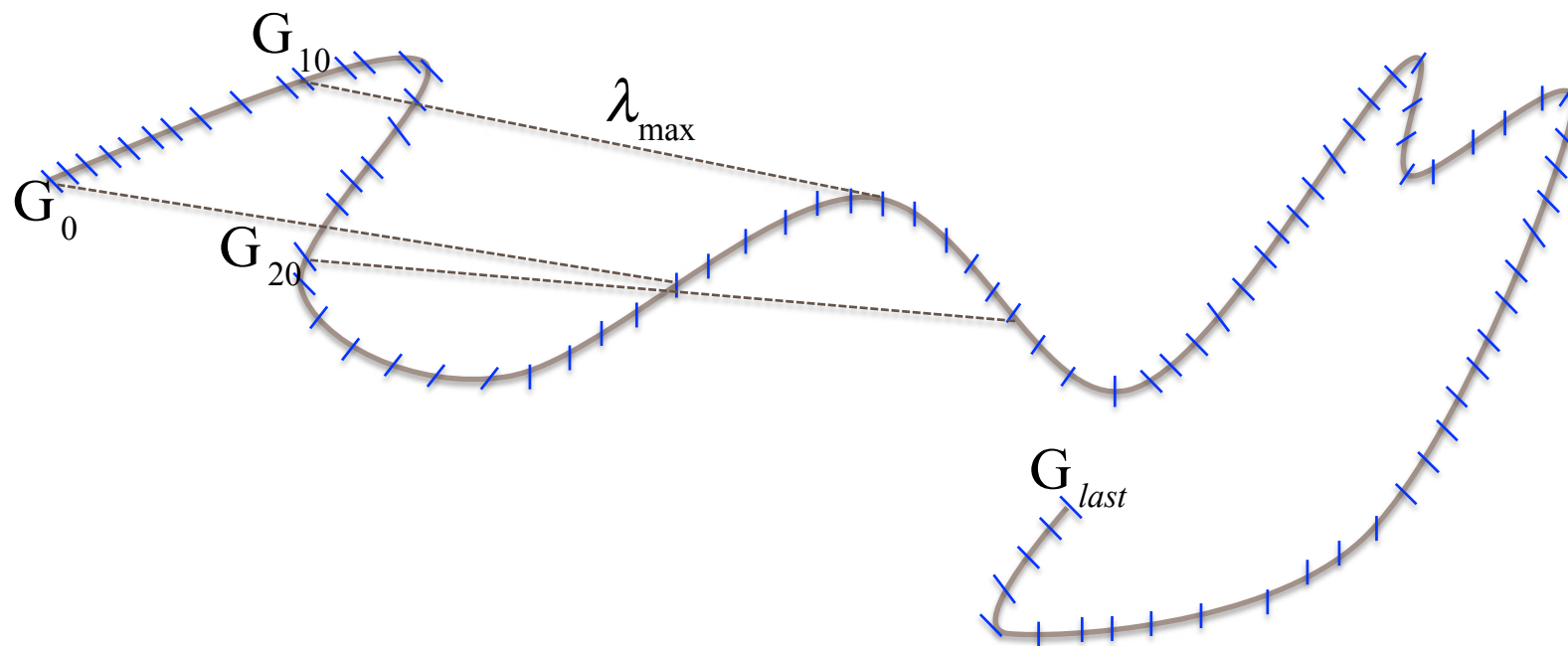
$t = 1000$

Office – Seq. # 0

$t = 1500$

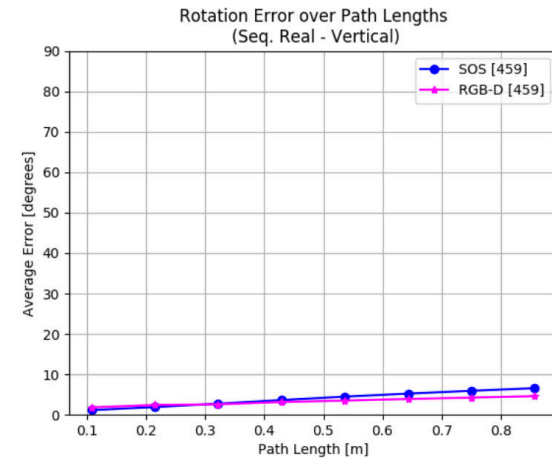
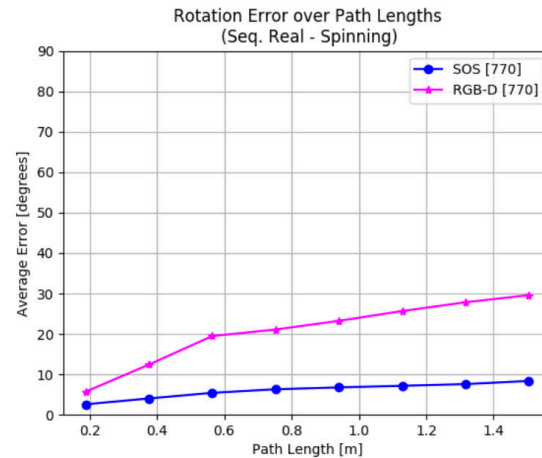
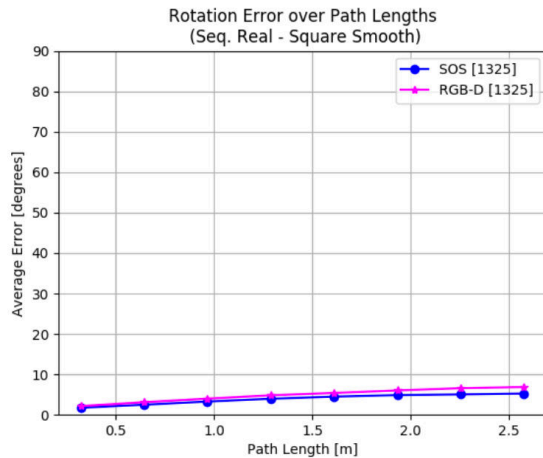


- Absolute Trajectory Error (ATE)
- Relative Pose Error (RPE)
 - 8 linearly spaced path lengths: $\{\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6, \lambda_7, \lambda_{\max}\}$
 - The max path length λ_{\max} is **1/3** of the entire path length.

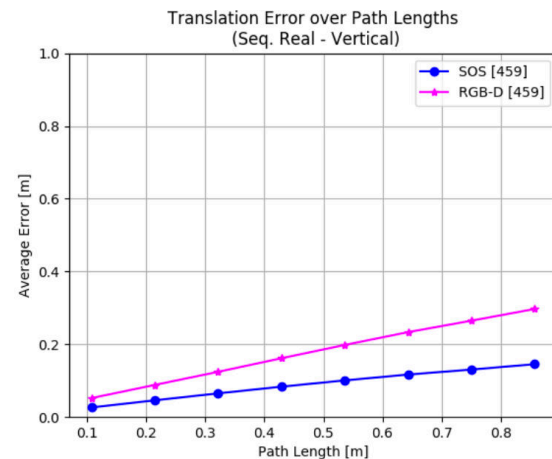
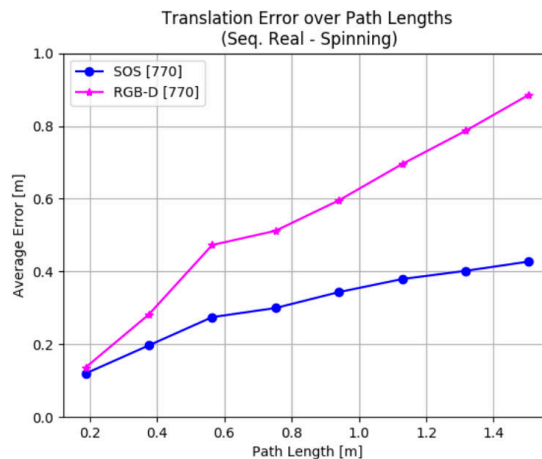
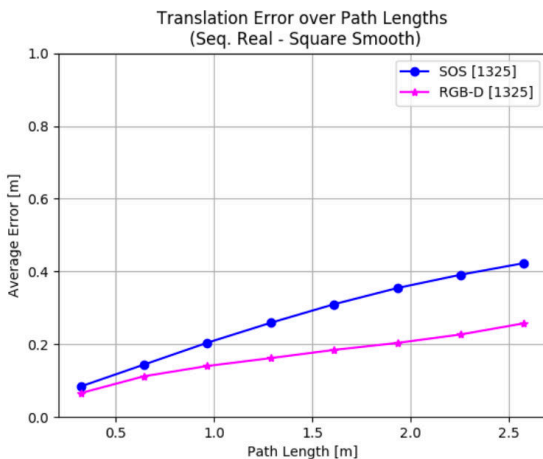


Results for “moving” rigs in a conventional form

RPE (Rotation)



RPE (Translation)



NOTE: All frames were considered for evaluation



VO Quantitative Evaluation

<Intro> <SOS> <GUMS> **<VO>**



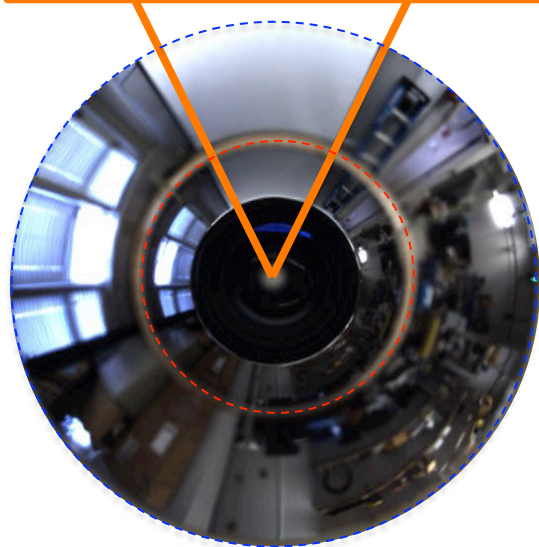
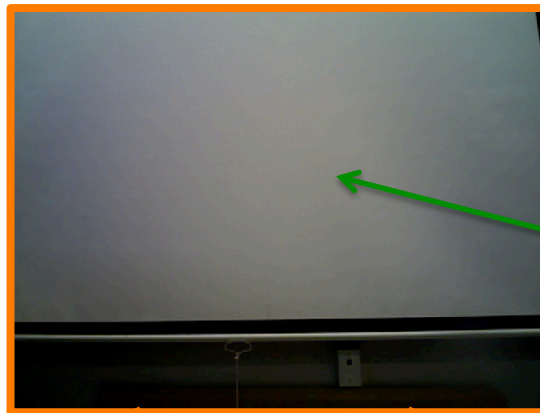
Results for “moving” rigs in a **conventional** form

Average absolute trajectory error (ATE) and relative pose error (RPE, normalized)

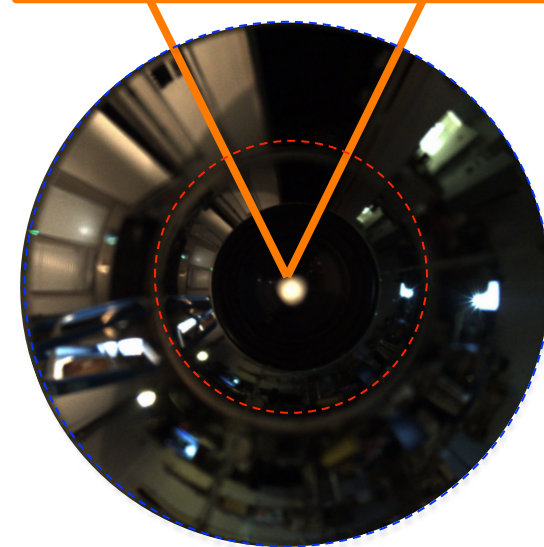
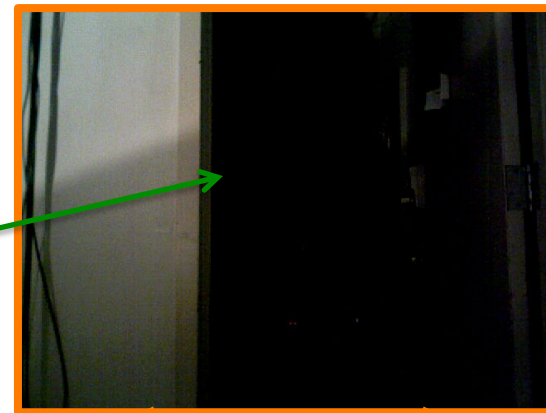
Sequence		ATE [m]		RPE (Translation) [%]		RPE (Rotation) [°/m]	
		SOS	RGB-D	SOS	RGB-D	SOS	RGB-D
Conventional	Square Small	0.12 ± 0.05	0.70 ± 0.23	25.94 ± 8.18	41.76 ± 78.21	3.46 ± 2.76	22.37 ± 45.52
	Square Smooth	0.12 ± 0.06	0.14 ± 0.11	20.51 ± 8.54	13.92 ± 7.89	3.29 ± 1.97	4.11 ± 2.51
	Spinning	0.30 ± 0.11	0.35 ± 0.08	42.60 ± 19.59	68.30 ± 80.08	8.64 ± 4.78	27.08 ± 36.18
	Vertical	0.04 ± 0.02	0.14 ± 0.06	19.86 ± 5.31	39.06 ± 16.12	8.68 ± 3.55	8.76 ± 6.05
	Free Style	0.14 ± 0.05	0.41 ± 0.14	31.34 ± 13.57	45.75 ± 54.99	9.65 ± 5.21	14.53 ± 20.35
	Hallway	0.95 ± 0.58	0.81 ± 0.56	262.53 ± 546.43	391.20 ± 763.28	10.14 ± 18.98	8.54 ± 12.61

NOTE: All frames were considered for evaluation

Into a Wall



Into the Dark

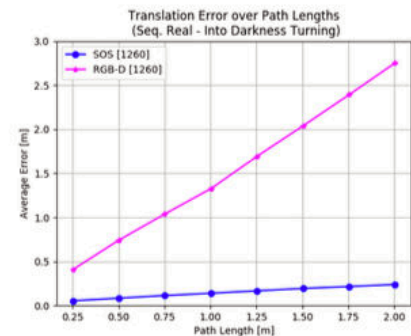
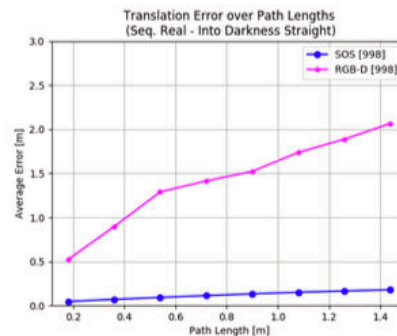
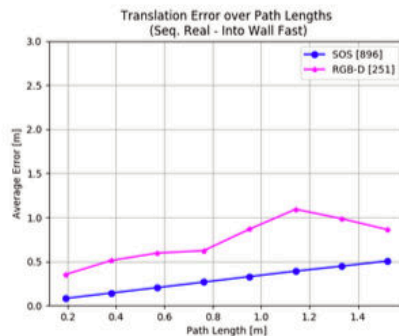
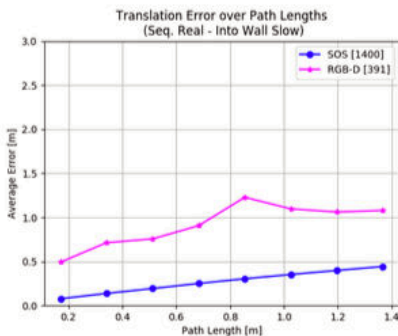
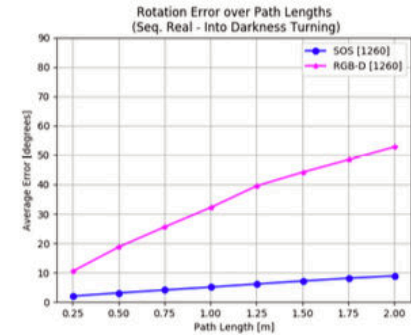
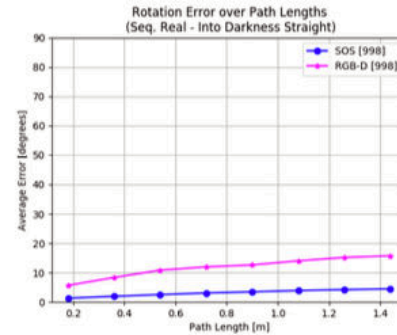
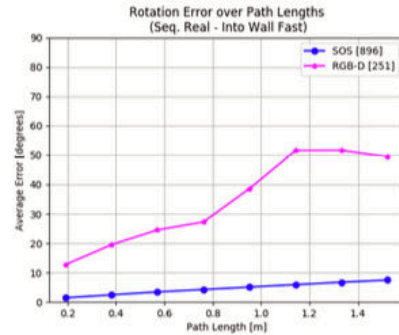
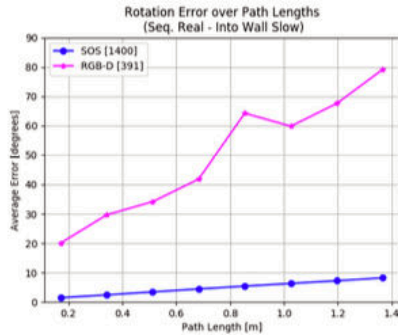


Lack of detectable features

Results for “moving” rigs in special feature-based circumstances

RPE (Rotation)

RPE (Translation)



	Sequence	ATE [m]		RPE (Translation) [%]		RPE (Rotation) [°/m]		Frames [#]	
		SOS	RGB-D	SOS	RGB-D	SOS	RGB-D	SOS	RGB-D
Special	Into Wall - Regular	0.13 ± 0.04	0.22 ± 0.08	37.70 ± 11.00	130.41 ± 79.68	6.70 ± 1.86	57.27 ± 42.25	1041	315
	Into Wall - Slow	0.09 ± 0.03	0.19 ± 0.09	37.21 ± 10.64	165.29 ± 106.22	6.72 ± 1.99	76.63 ± 65.46	1400	391
	Into Wall - Fast	0.09 ± 0.04	0.18 ± 0.09	36.02 ± 9.61	115.06 ± 79.37	5.83 ± 1.91	47.08 ± 36.90	896	251
	Into Wall - Curvy	0.28 ± 0.08	0.22 ± 0.11	35.45 ± 14.35	136.35 ± 123.50	6.39 ± 2.82	77.65 ± 81.61	838	309
	Into Dark - Straight	0.06 ± 0.03	0.53 ± 0.24	16.87 ± 6.31	213.43 ± 218.62	4.54 ± 1.99	19.38 ± 14.02	998	554
	Into Dark - Turning	0.13 ± 0.06	0.73 ± 0.23	14.92 ± 6.07	141.20 ± 177.83	5.50 ± 2.36	32.95 ± 37.47	1260	1260

NOTE: All frames were considered for evaluation



VO in Dynamic Environments



<Intro> <SOS> <GUMS> **<VO>**

Results for “static” rigs in dynamic environments

Prox [m]	Peop [#]	Translation Error [m]		Rotation Error [°]	
		SOS	RGB-D	SOS	RGB-D
1	1	0.021 ± 0.008	0.279 ± 0.207	0.310 ± 0.120	5.230 ± 3.160
1	2	0.021 ± 0.006	0.600 ± 0.348	0.380 ± 0.080	8.720 ± 6.000
1	4	0.047 ± 0.017	1.614 ± 0.768	0.610 ± 0.240	21.320 ± 10.820
2	1	0.015 ± 0.005	0.586 ± 0.330	0.230 ± 0.070	7.940 ± 4.220
2	2	0.017 ± 0.007	1.049 ± 0.404	0.250 ± 0.120	17.300 ± 9.310
2	4	0.030 ± 0.008	2.247 ± 0.982	0.570 ± 0.270	13.400 ± 6.370
3	1	0.013 ± 0.004	1.029 ± 0.632	0.140 ± 0.040	11.940 ± 8.900
3	2	0.022 ± 0.005	1.728 ± 0.598	0.340 ± 0.090	24.240 ± 13.100
3	4	0.028 ± 0.007	1.854 ± 0.681	0.460 ± 0.110	13.710 ± 12.780
Var	2	0.049 ± 0.021	0.481 ± 0.260	0.900 ± 0.310	17.980 ± 10.900
Var	Var	0.374 ± 0.193	4.487 ± 1.261	5.630 ± 3.600	39.390 ± 11.120

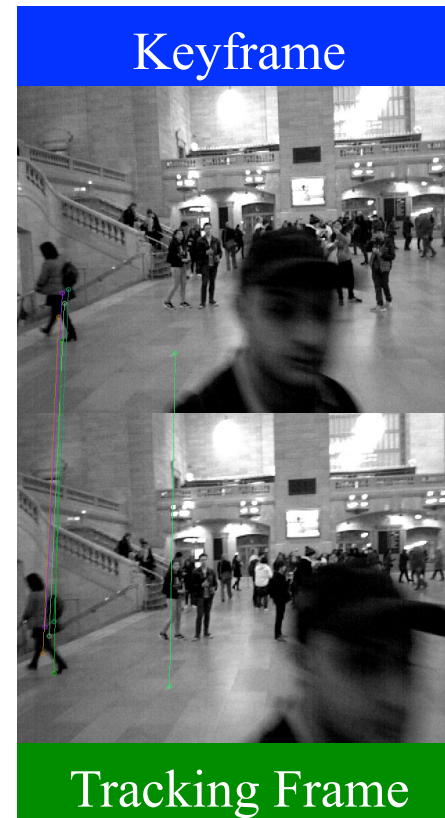
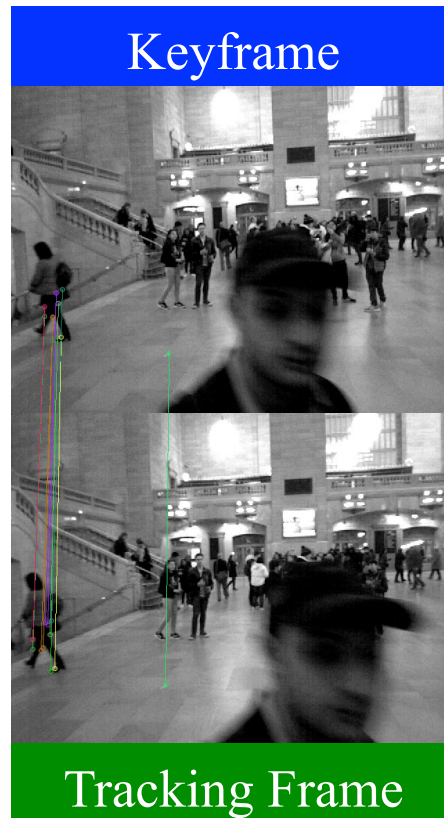
VO in Dynamic Environments

<Intro> <SOS> <GUMS> <VO>

Results for “moving” rigs in **highly-dynamic** environments

OKAY

Next frame: LOST



Tracking **lost** for **RGB-D camera** after the 191st frame

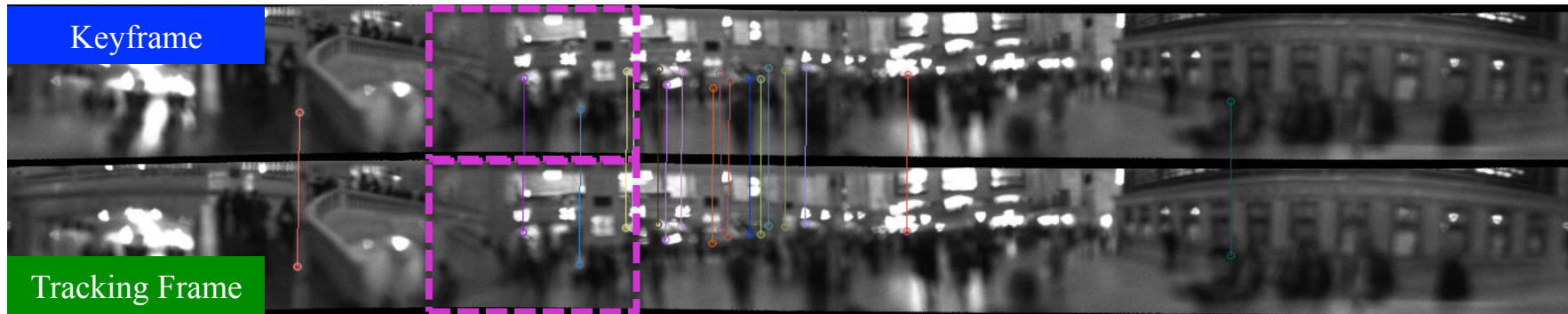
Reason: Less than **3** consistent features for **P3P**

VO in Dynamic Environments

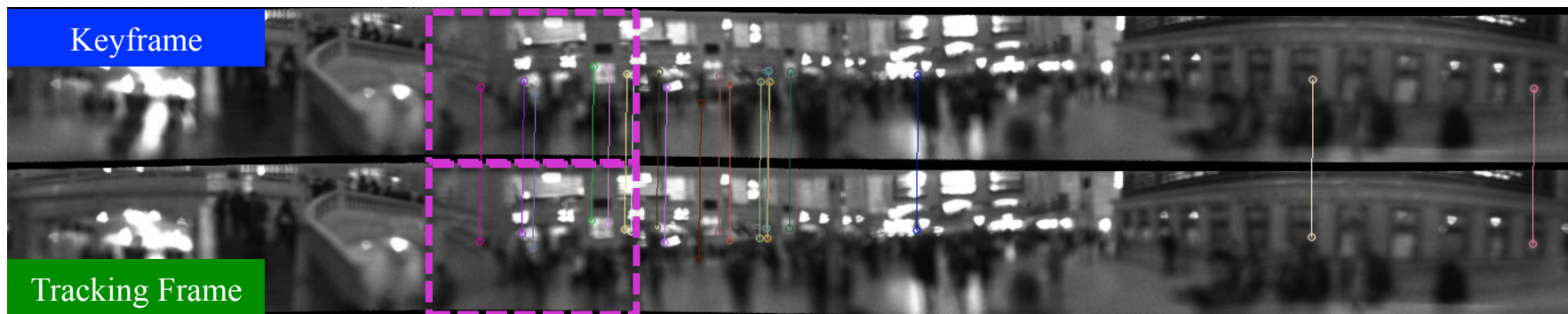
<Intro> <SOS> <GUMS> <VO>

Results for “moving” rigs in highly-dynamic environments

OKAY



Next frame: OKAY

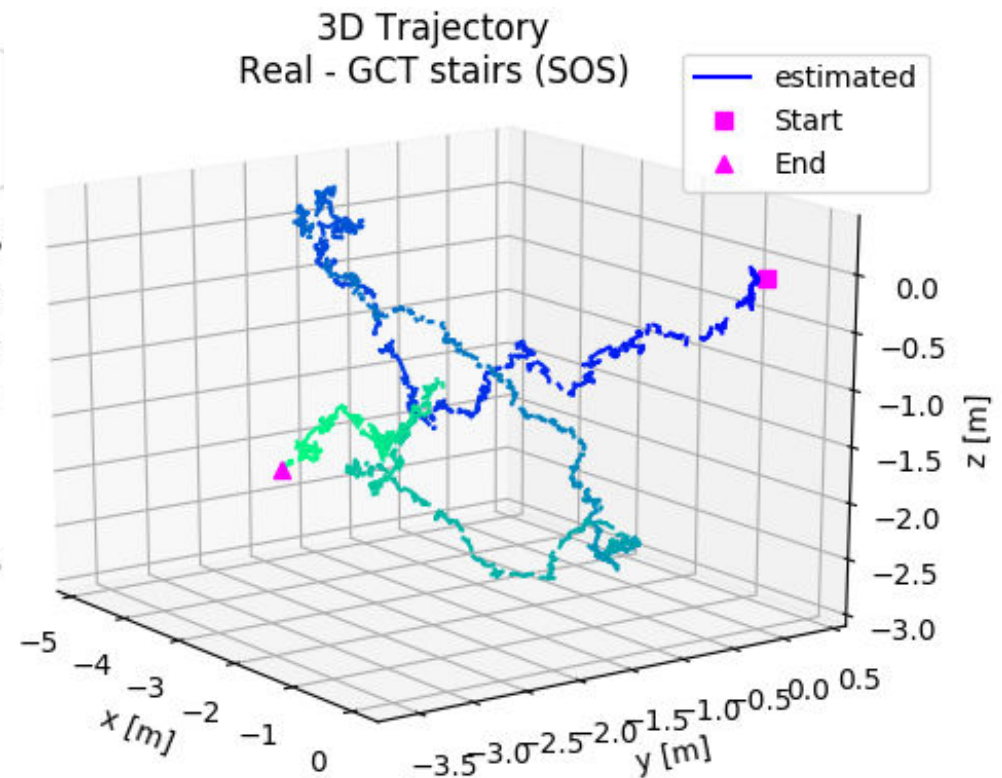
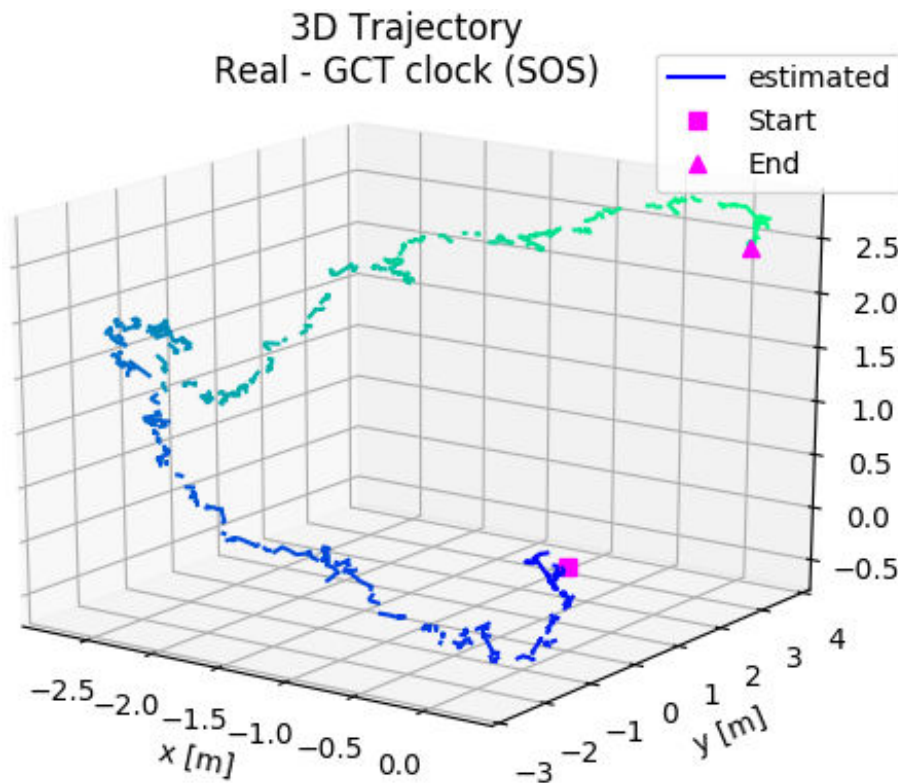


Panoramic images (top view)

VO in Dynamic Environments

<Intro> <SOS> <GUMS> <VO>

Qualitative results for “moving” rigs in highly-dynamic environments



[Video Link](#)

NOTES: 1) Showing only keyframe positions; 2) These trajectories are not fit to the ground plane.



Thesis Summary of Contributions



- Presented two **practical configurations** to achieve *omnistereo* vision with a **single camera**:
 - 1) Spherical SOS
 - 2) Hyperbolic SOS
- Introduced **GUMS** as a “Generalized Unified Model for Stereo” omnidirectional systems:
 - **Simple** yet **effective** model
 - **Optimal** parameters for a “**coupled**” projective function.
 - **Practical** calibration method performed via *control-points* imaged around the rig
- Demonstrated the 3D metric **visual odometry** (VO) capabilities of the single- camera SOS:
 - **3D pose** was estimated *geometrically* via a **feature-based** tracking method
 - Compared its **performance** against a traditional range sensor (i.e., an **RGB-D camera**).
 - Generated several real and synthetic **datasets** with **ground-truth** pose information
- Improved the **tracking accuracy** of a **single camera** through the **direct** method:
 - In terms of **high-dimensional features** (channels) generated via
 - a) Conventional hand-crafted features
 - b) Features extracted from convolutional neural networks



Relevant Publications



- Igor Labutov, **Carlos Jaramillo**, and Jizhong Xiao. 2011. “*Generating near-Spherical Range Panoramas by Fusing Optical Flow and Stereo from a Single-Camera Folded Catadioptric Rig.*” *Machine Vision and Applications* 24 (1).
- **Carlos Jaramillo**, Roberto G Valenti, Ling Guo, and Jizhong Xiao. 2016. “*Design and Analysis of a Single-Camera Omnistereo Sensor for Quadrotor Micro Aerial Vehicles (MAVs).*” *Sensors* 16 (2).
- **Carlos Jaramillo**, Roberto G. Valenti, and Jizhong Xiao. 2016. “*GUMS: A Generalized Unified Model for Stereo Omnidirectional Vision (Demonstrated Via a Folded Catadioptric System).*” In 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2528–33. Daejeon, Korea.
- **Carlos Jaramillo**, Yuichi Taguchi, and Chen Feng. 2017. “*Direct Multichannel Tracking.*” In IEEE International Conference on 3D Vision. Qingdao, China.
- **Carlos Jaramillo**, Liang Yang, J. Pablo Muñoz, Yuichi Taguchi, and Jizhong Xiao. 2018. “*Visual Odometry with a Single-Camera Stereo Omnidirectional System.*” In IEEE RA-Letters. Article **submitted** in May 9, 2018.



Thank You



Q



A