

ICCV 2025

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# Correspondence-Free Fast and Robust Spherical Point Pattern Registration

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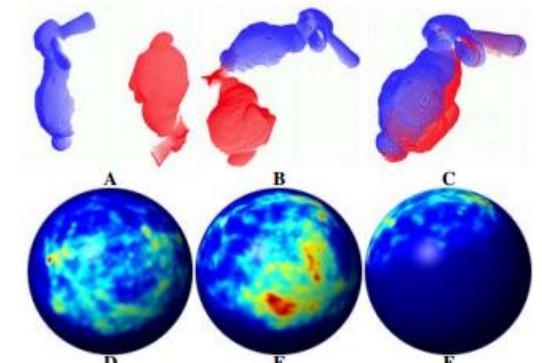
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# Background & Motivation

Many signals are inherently spherical  
(omnidirectional images, earth maps etc.)

In the past, spherical pattern matching was used for:

- Point cloud registration (global alignment on  $SO(3)$ )
- Spherical image registration (rotation estimation)



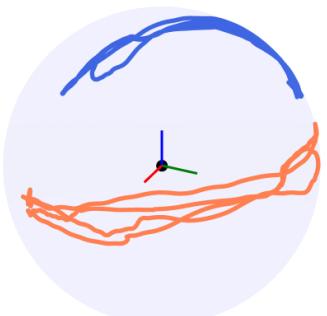
[Makadia et.al]

# Background & Motivation

In spherical cross-correlation, spherical patterns are treated as functions

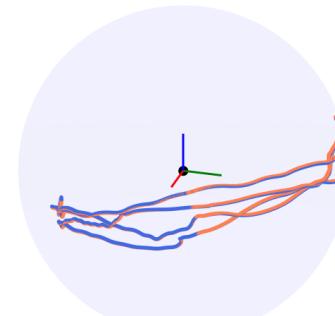
We treat spherical pattern matching as point pattern registration on the surface of a unit sphere

Unregistered



Source Pattern   
Template Pattern

Registered



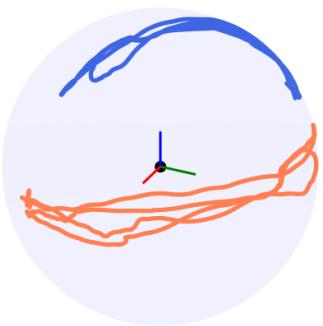
Spherical Point Pattern Matching Algorithm



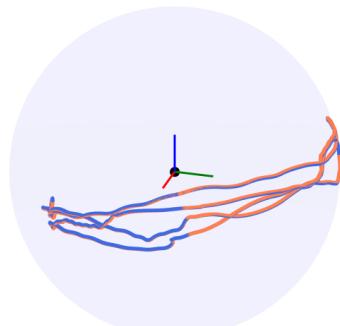
# Background & Motivation

One to One Correspondence (easy)  
*[closed form solution exists]*

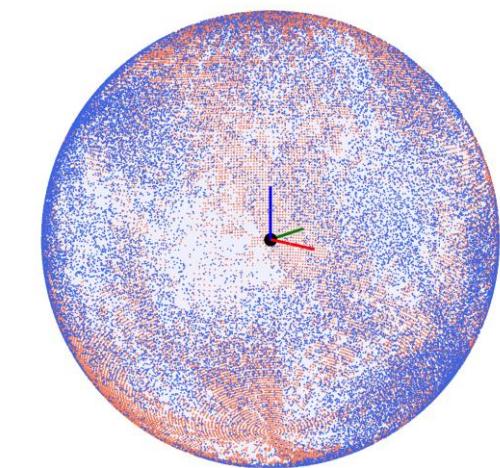
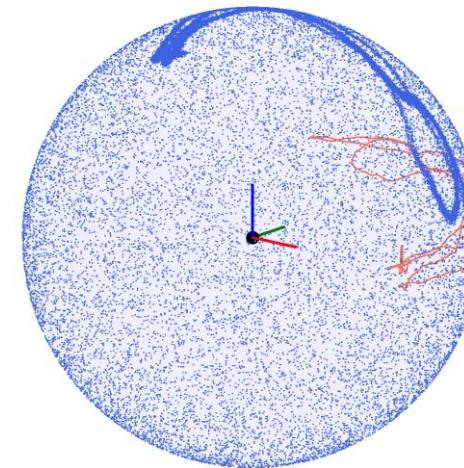
Unregistered



Registered



The problem becomes challenging under large rotations, heavy noise/outliers, or complex patterns.

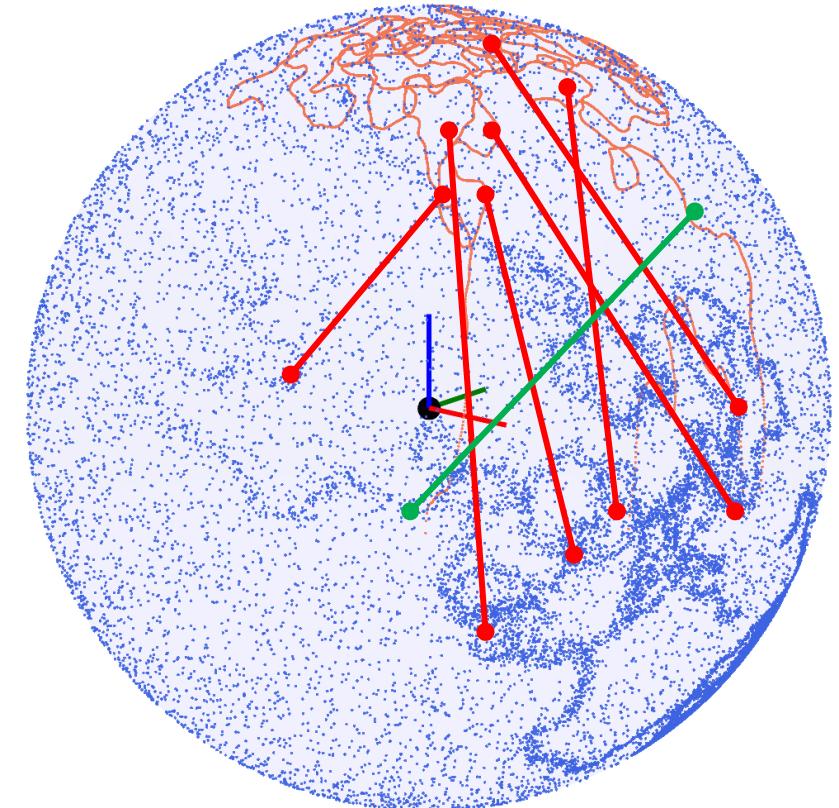


# Background & Motivation

## Corresponded based Methods

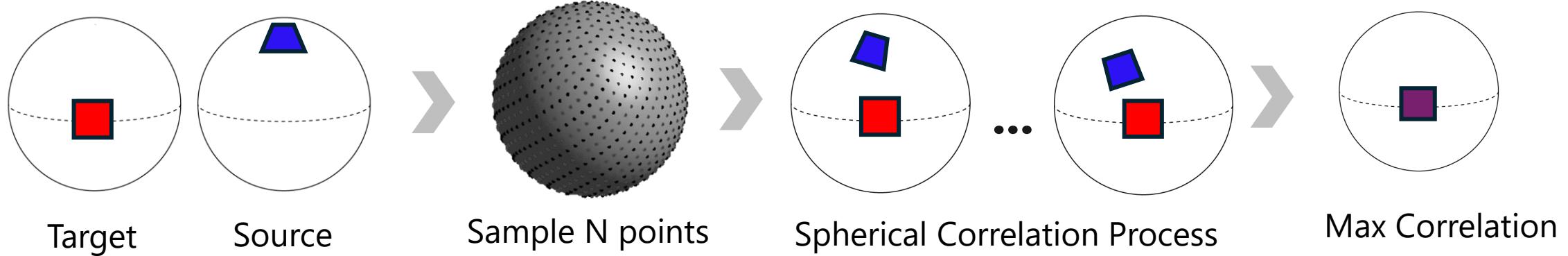
Finding reliable correspondences in spherical patterns with noise and outliers is extremely challenging. Due to

- lack of geometric variation
- overlapping regions, and inherent symmetries



# Background & Motivation

## Spherical Correlation Based Methods



Spherical cross-correlation is expensive; runtime grows rapidly with the rotational sampling, spherical harmonic bandlimit.

# Methods

(Overview)

We developed 3 Algorithms

Algorithm 1: SPMC (Spherical Pattern Matching by Correlation)

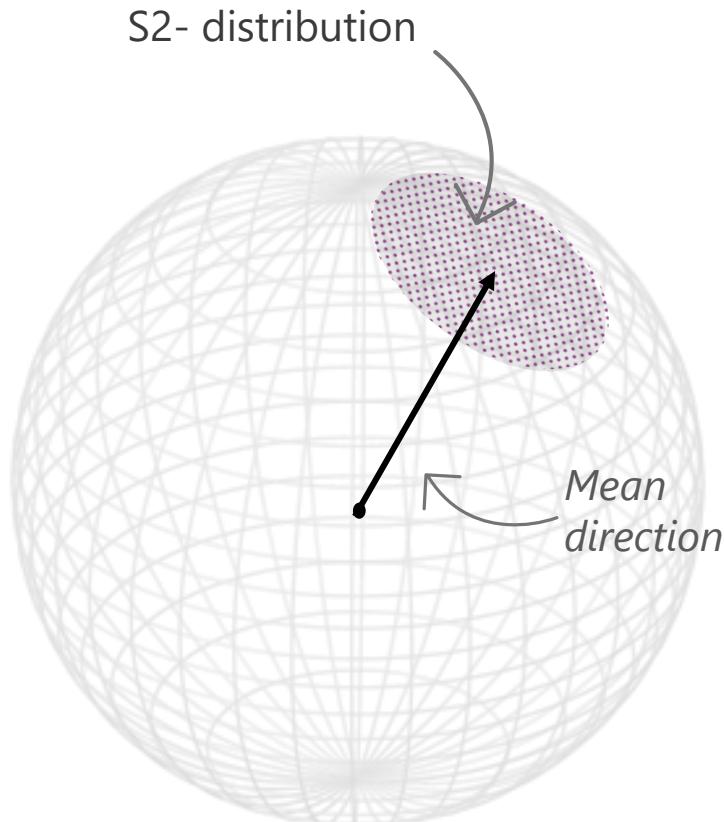
Algorithm 2: FRS (Fast Rotation Search)

Algorithm 3: SPMC + FRS (combines the first two)

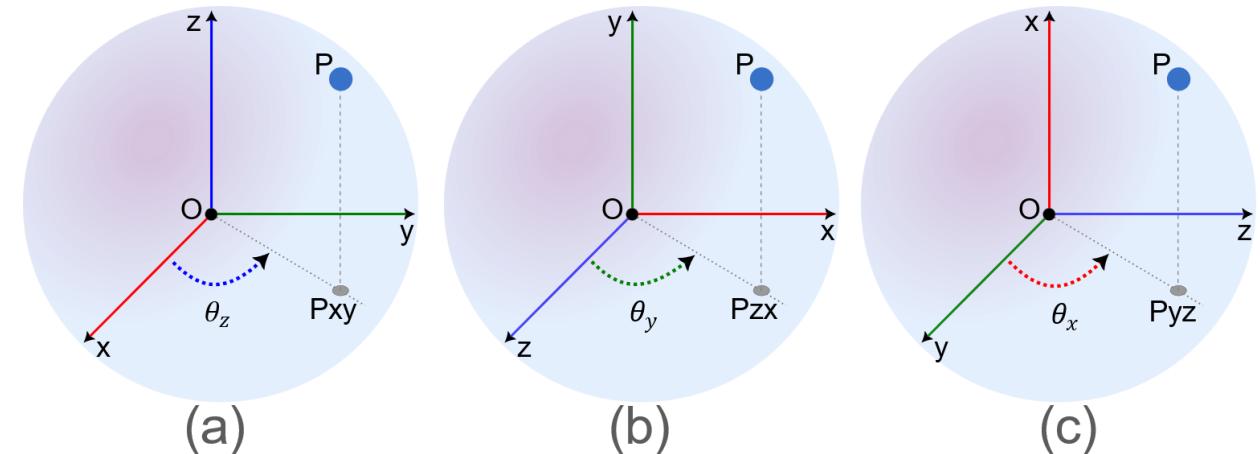
# Methods

(Terminologies)

## Mean Direction of Spherical Pattern



## Axis Direction Angles of an S2 Point

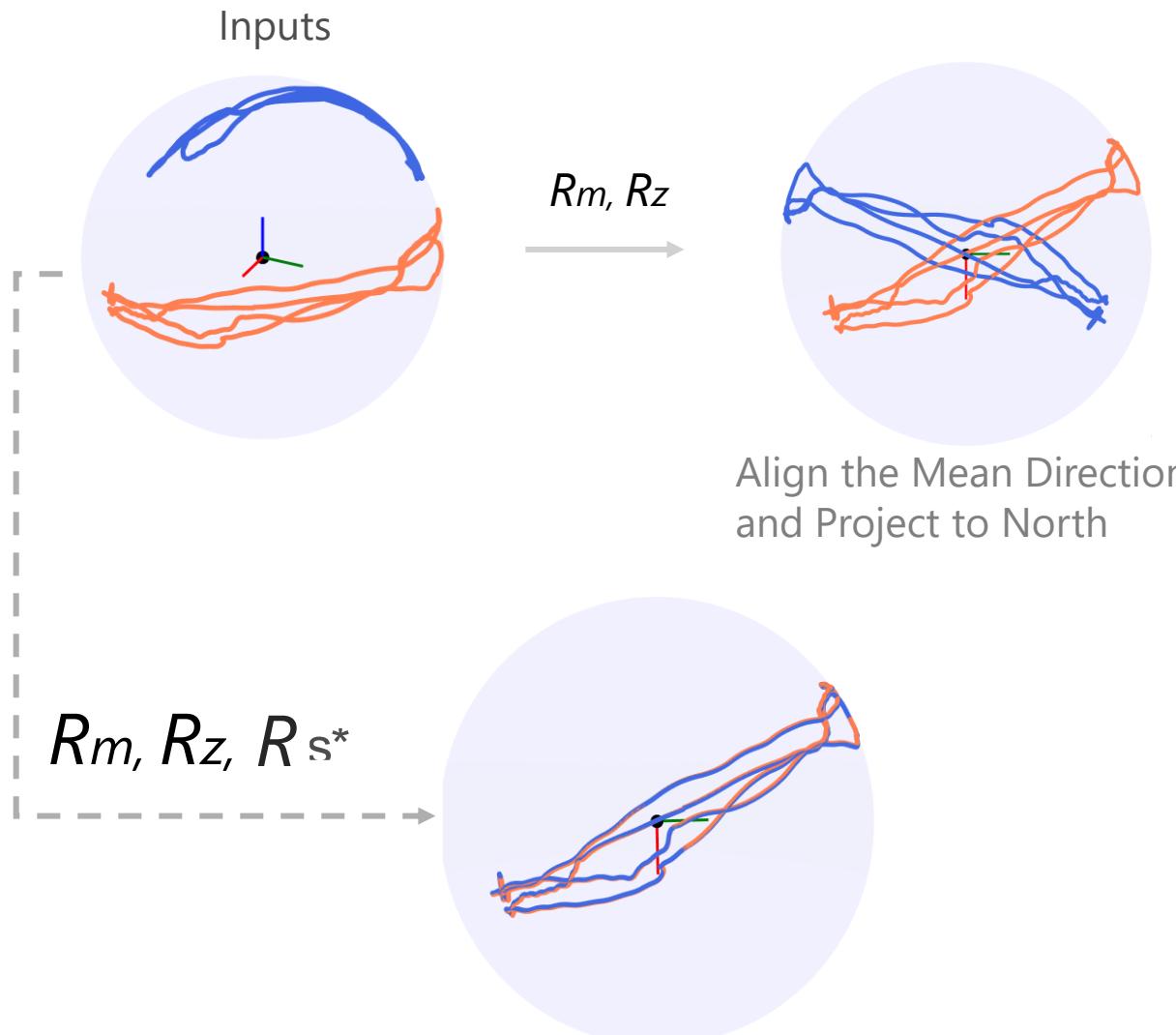


Template Pattern: 

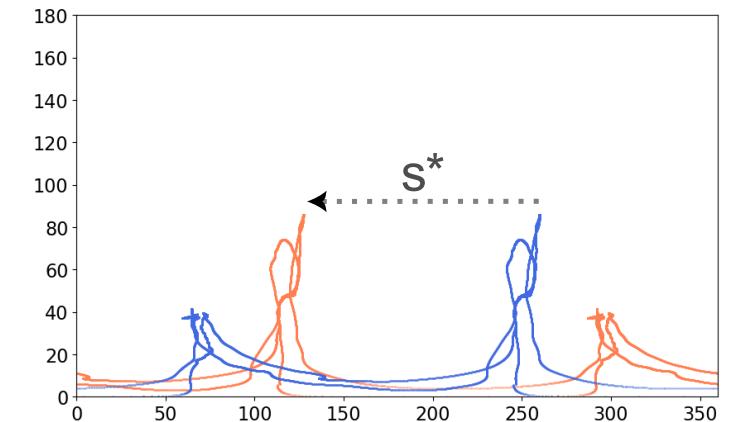
Source Pattern: 

# Methods

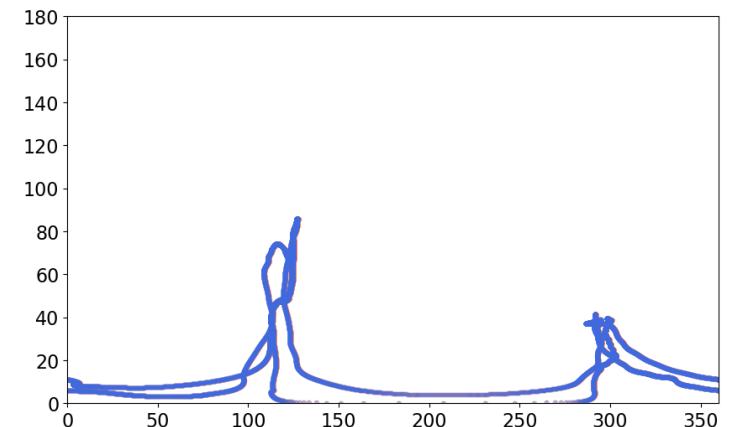
## Algorithm 1: SPMC



2D Projection and 1D correlation with circular shift



$R s^*$

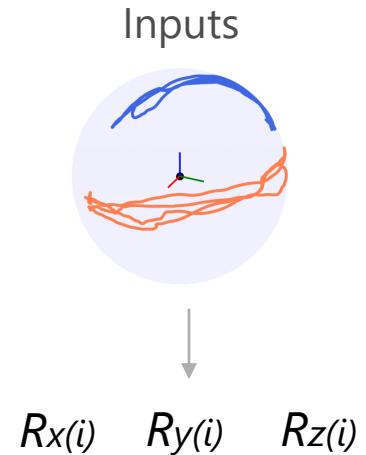


# Methods

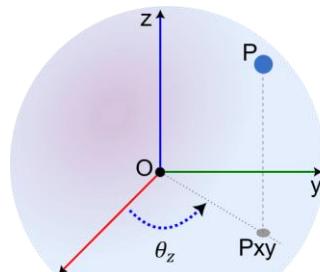
Algorithm 2: FRS

Template Pattern: 

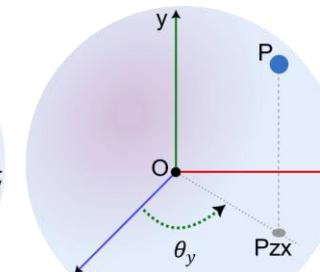
Source Pattern: 



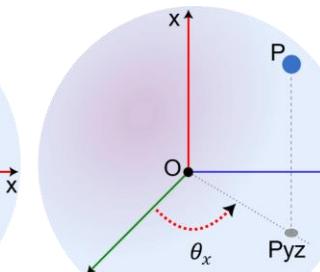
Iteration (i)



(a)

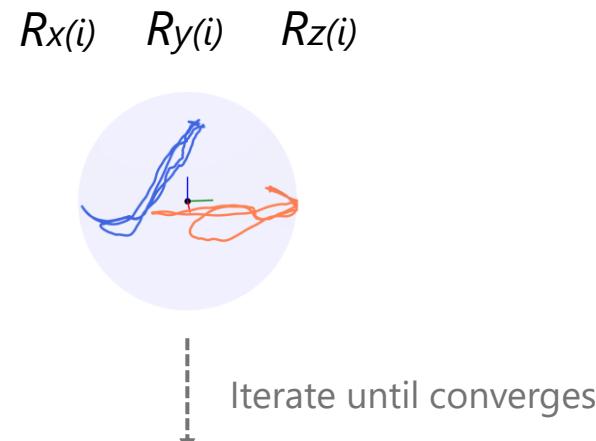


(b)



(c)

Axis Direction Angles



x-hist



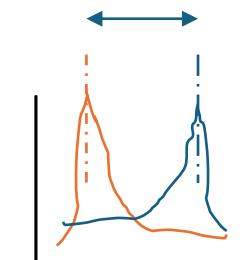
y-hist



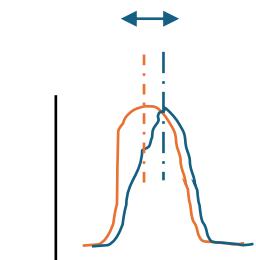
z-hist



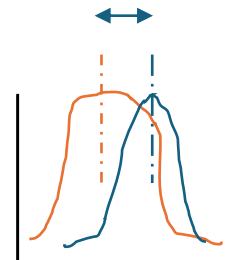
$R_x(i)$



$R_y(i)$



$R_z(i)$



Horizontal Bins (360)  
Vertical Bins (180)

# Methods

## Algorithm 3: SPMC+ FRS

### Algorithm 1: SPMC

- Mean direction is sensitive to when noise and outliers are significant

### Algorithm 2: FRS

- Sensitive to initialization

### Algorithm 3: SPMC +FRS

- SPMC provides a good initialization. FRS converges even faster

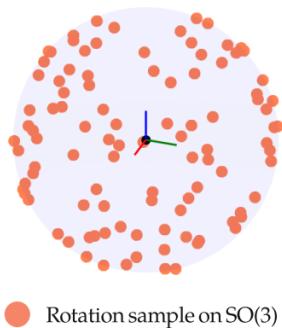
# Novel Synthetic Dataset

## Robust Vector Alignment Dataset

5 Random patterns (A1,..., A5)

7 Levels of Noise and Outliers (B1,..,B7)

100 Random Rotation



A5B1: noise  $\sigma=0.0$ , outliers 0%

A5B2: noise  $\sigma=0.01$ , outliers 10%

A5B3: noise  $\sigma=0.01$ , outliers 50%

A5B4: noise  $\sigma=0.01$ , outliers 90%

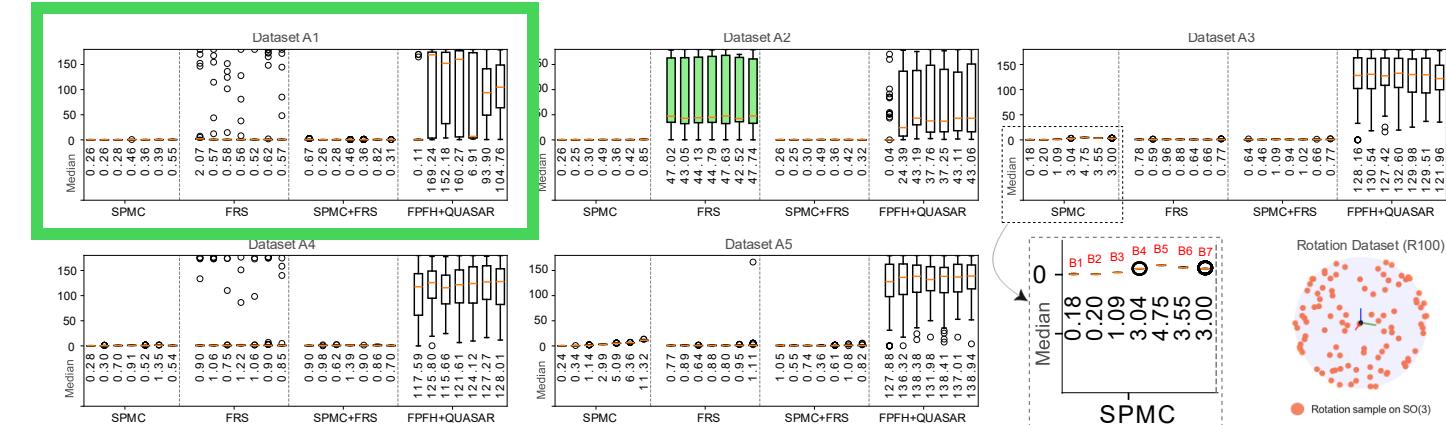
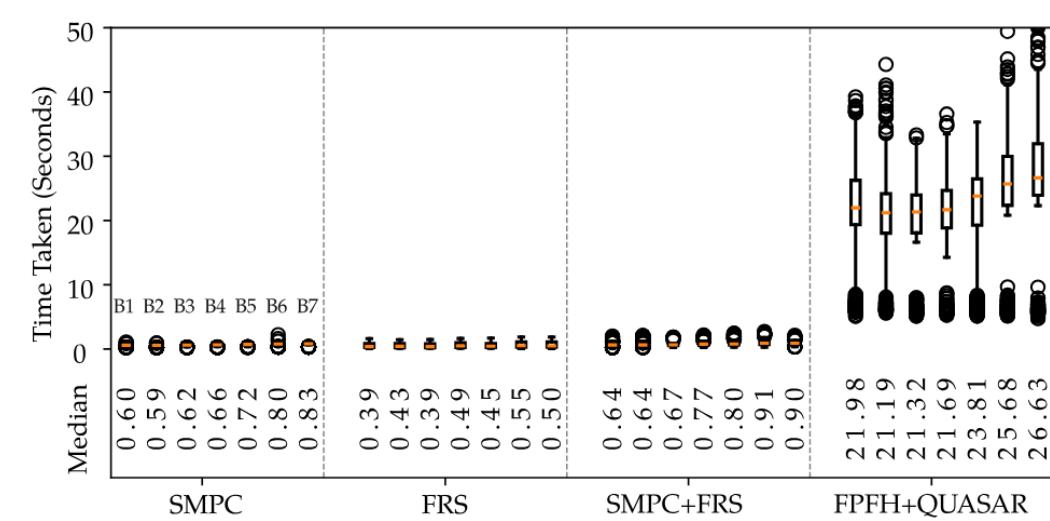
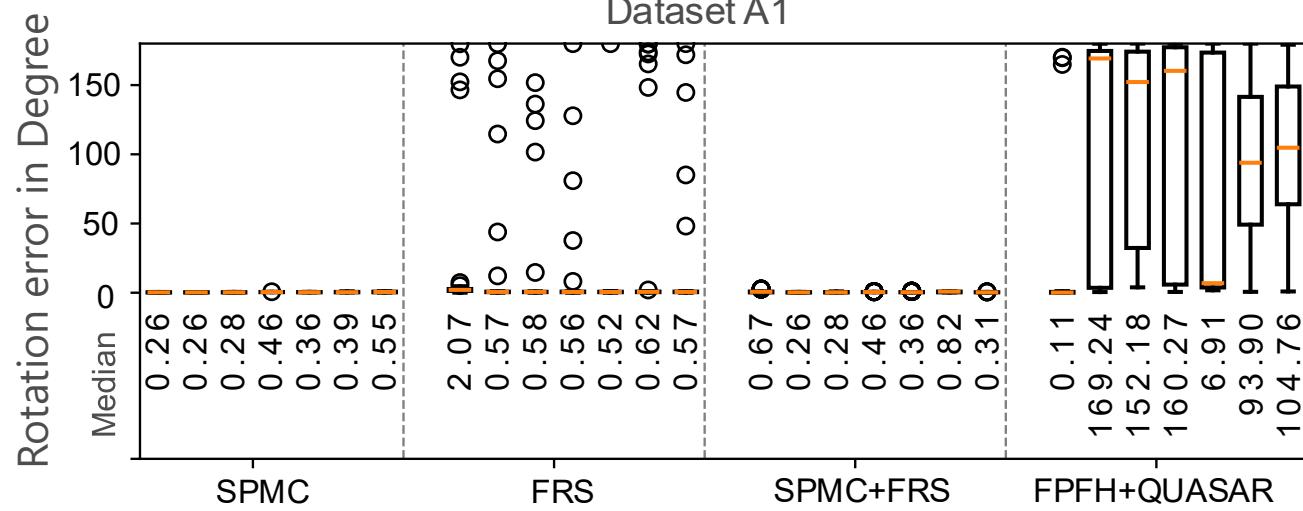
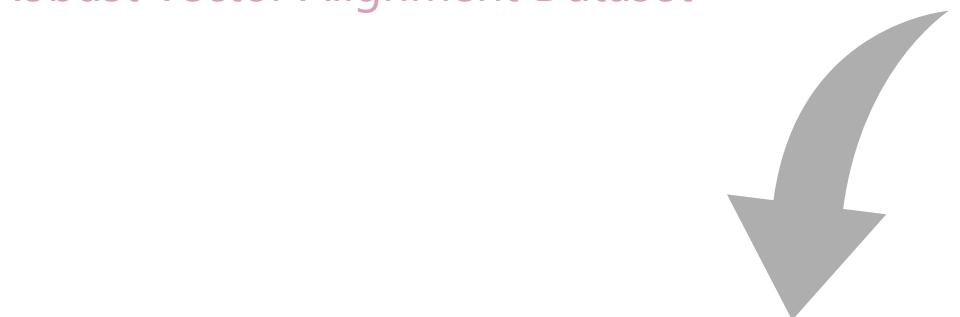
A5B5: noise  $\sigma=0.1$ , outliers 10%

A5B6: noise  $\sigma=0.1$ , outliers 50%

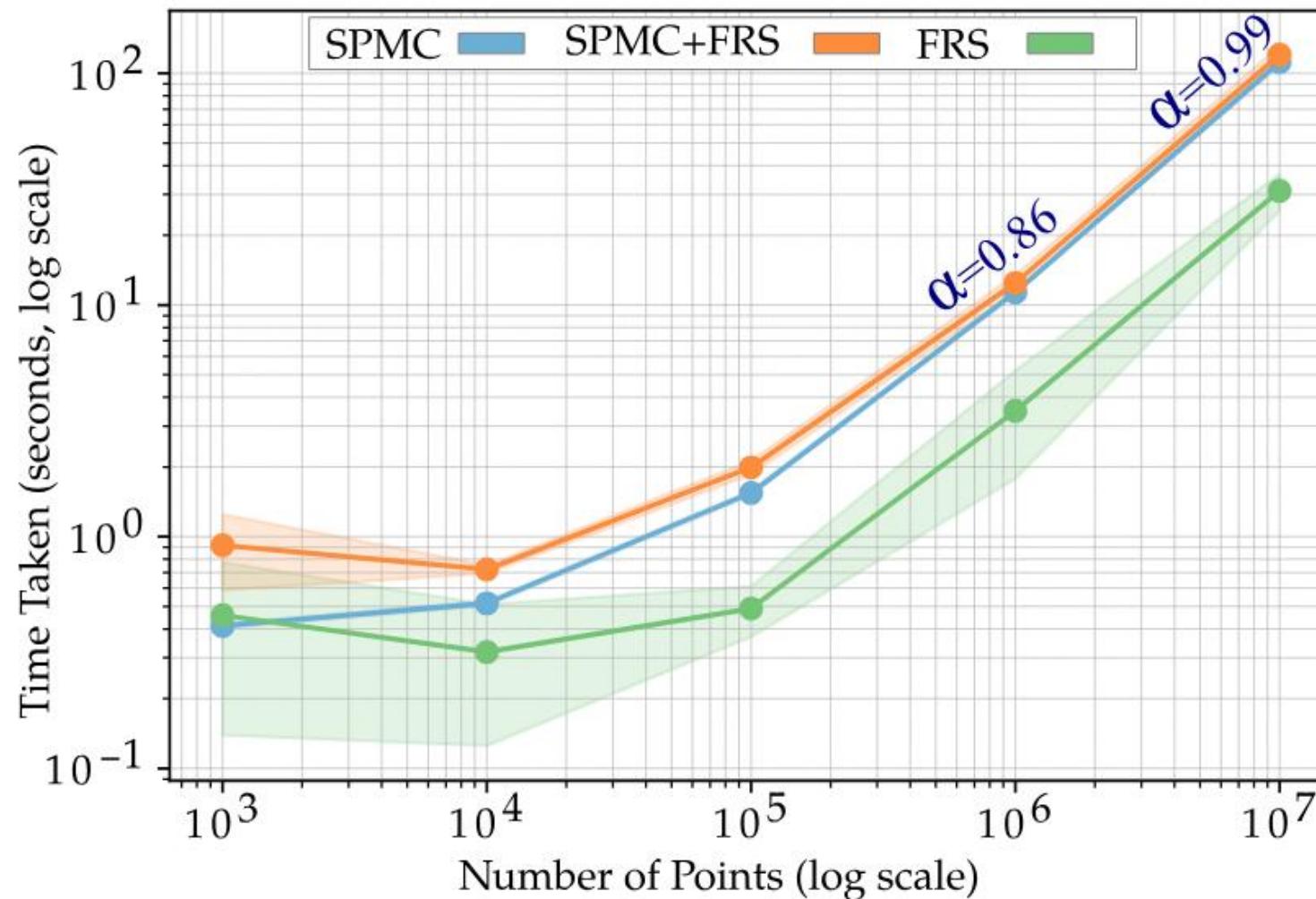
A5B7: noise  $\sigma=0.1$ , outliers 90%

## Results

# Robust Vector Alignment Dataset



# Time Complexity: $\sim O(N)$



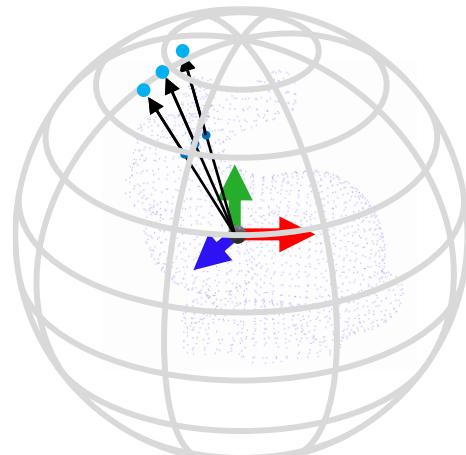
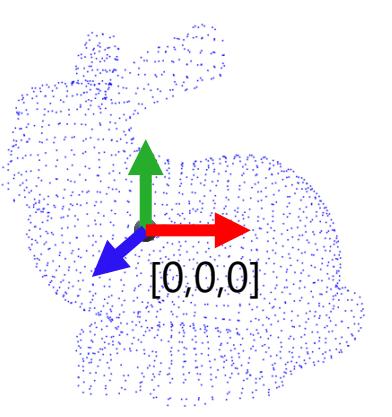
# Application 1: Point Cloud Registration

Rotational alignment (our method)

Translation estimation [adaptive voting (e.g TEASER) or centroid shift (for complete to complete)]

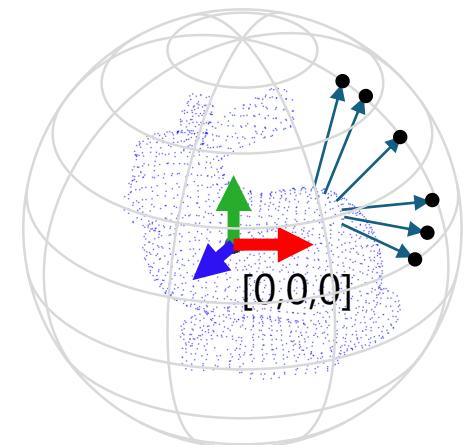
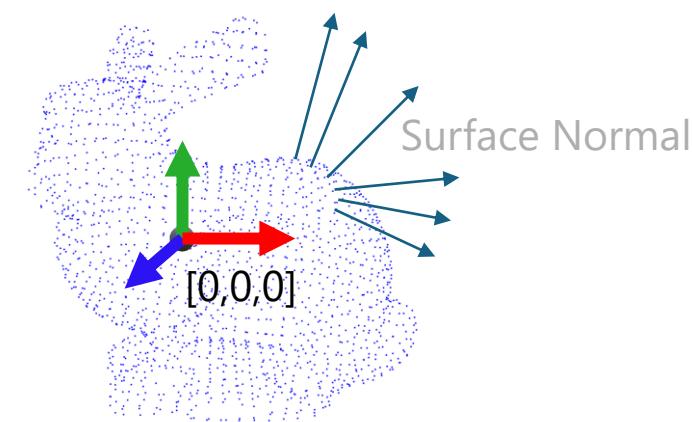
## Spherical Representation of Point Cloud

### 1) CASE (Centroid Aware Spherical Embedding)



Applicable if we know the complete geometry of the objects (complete to complete registration)

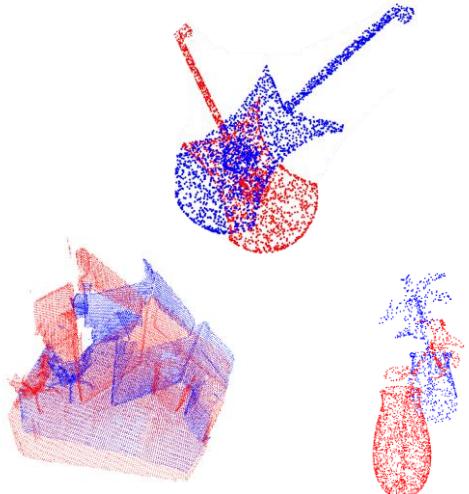
### 2) EGI (Extended Gaussian Image)



Can generate spherical signal for partial point cloud

# Application 1: Point Cloud Registration

Point Clouds



Spherical Embedding

**CASE**

*(Centroid Aware Spherical Embedding)*

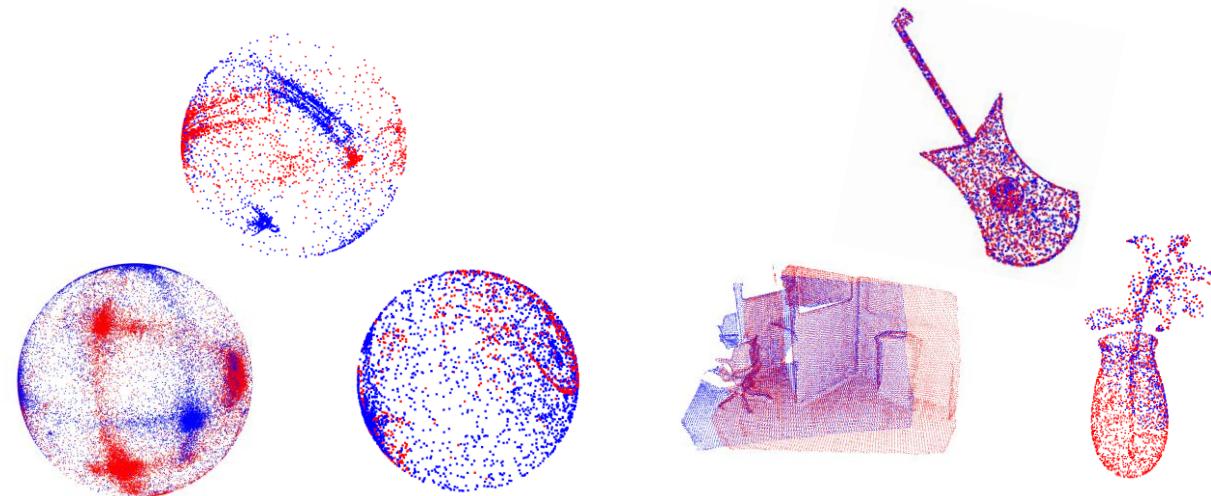
Complete to Complete

**EGI**

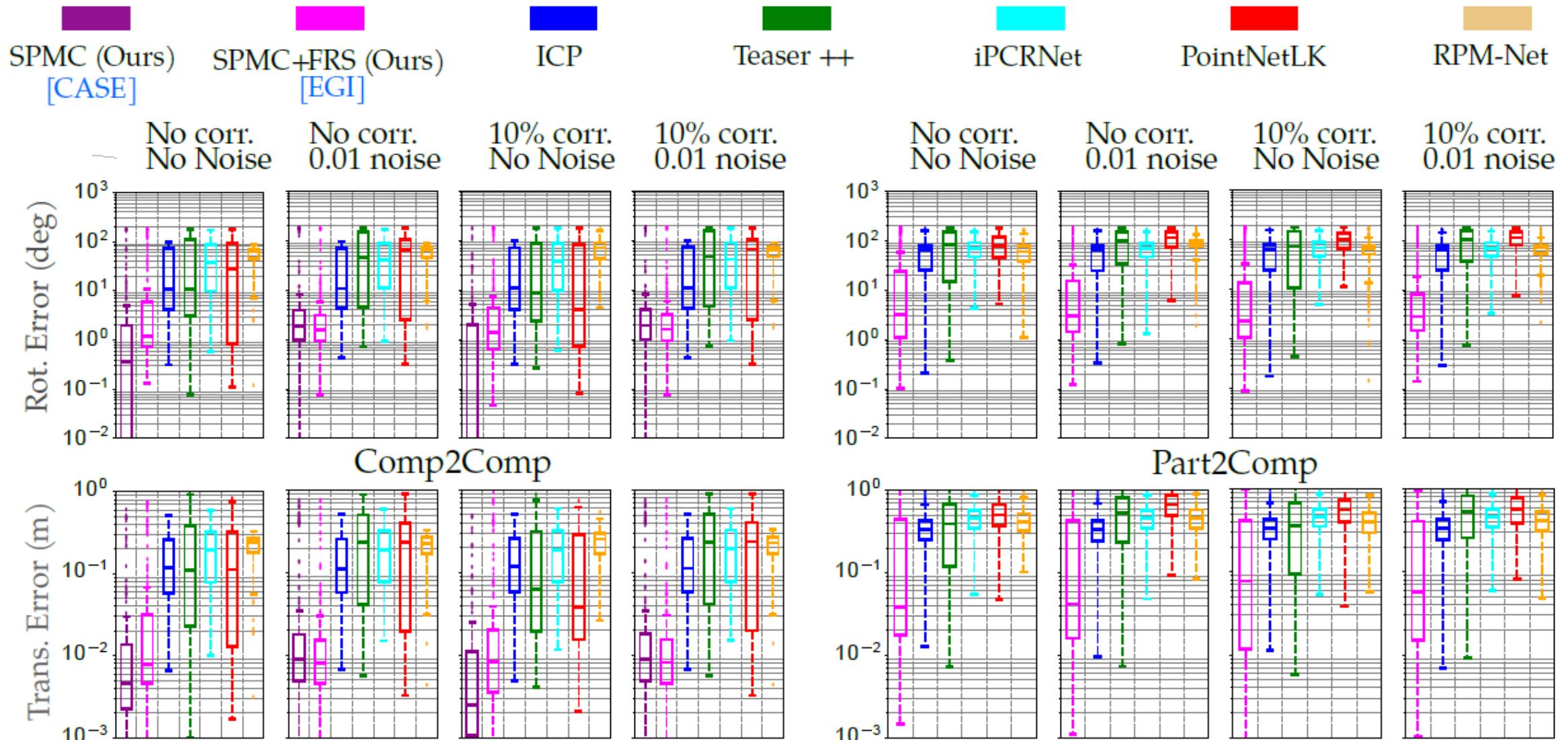
*(Extended Gaussian Image)*

Partial to Partial,  
Partial to Complete

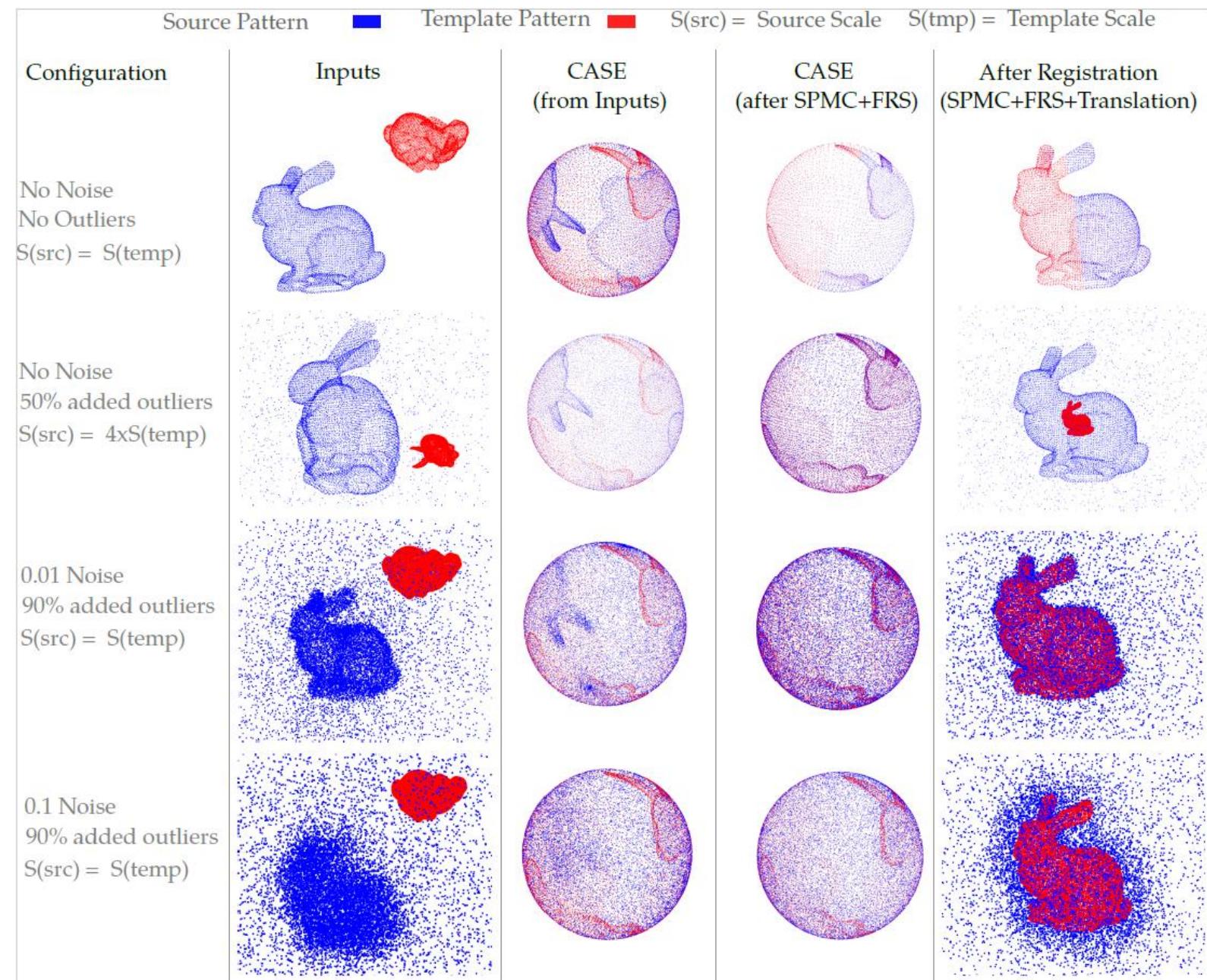
After Registration



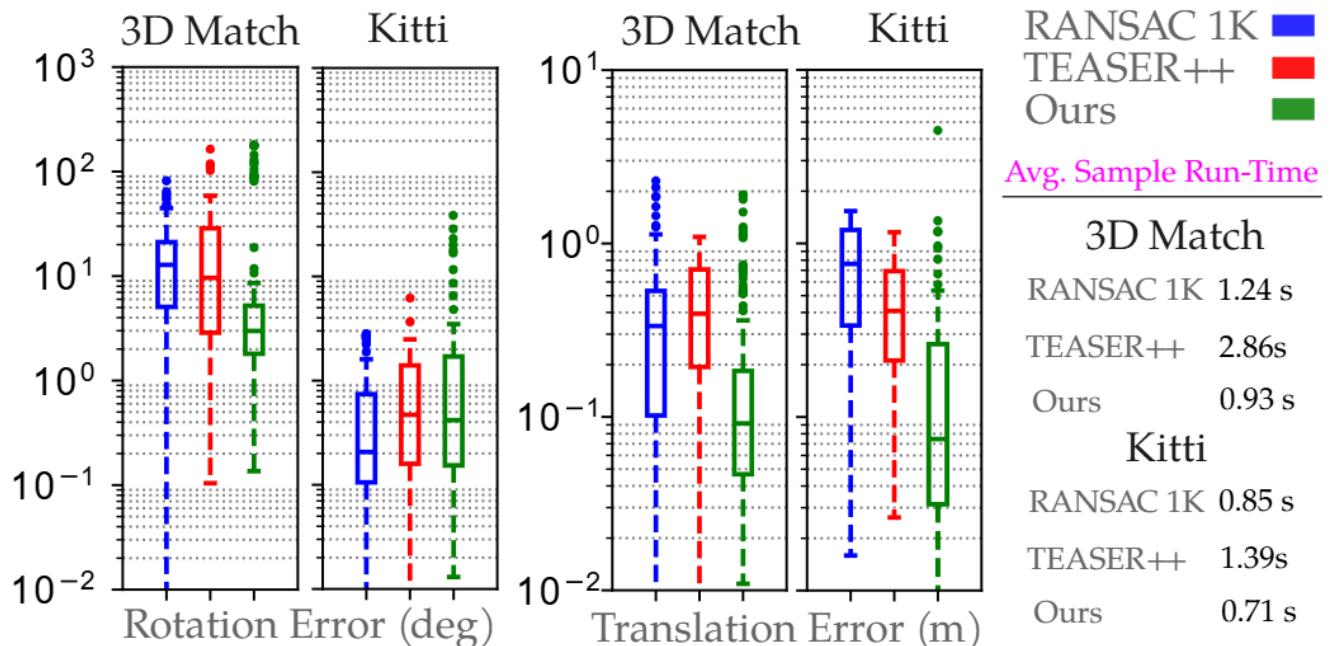
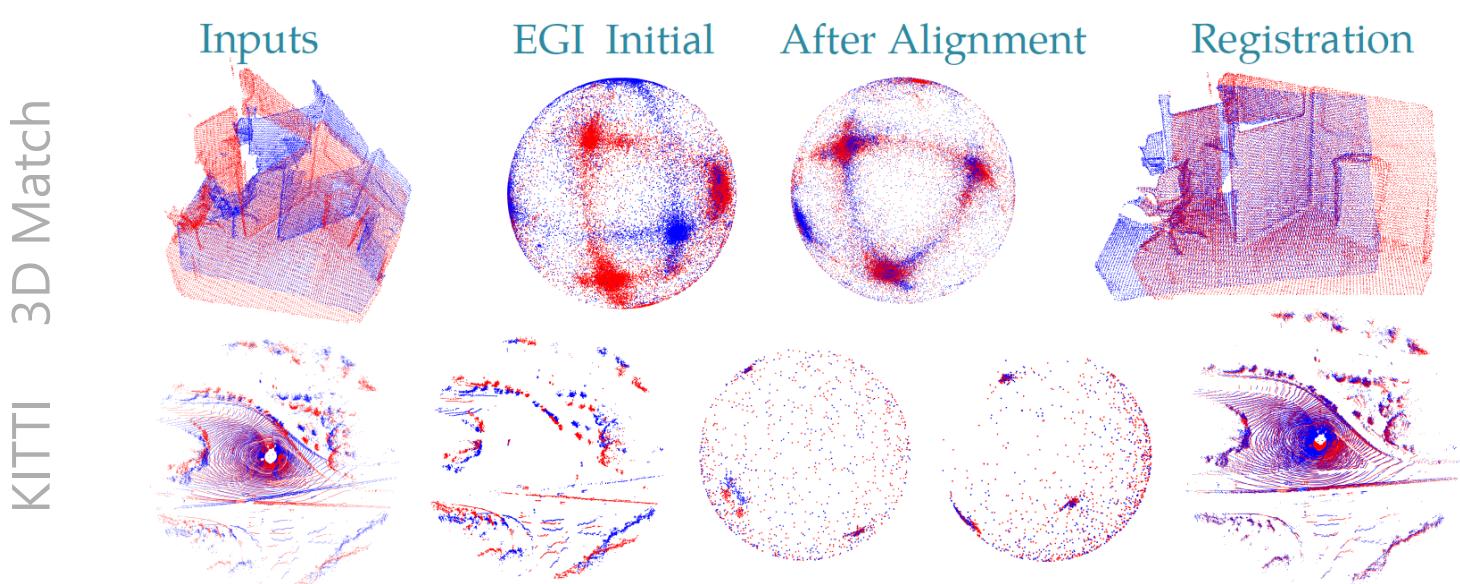
# Quantitative Evaluation: ModelNet40



## Qualitative Evaluation: Bunny Dataset (complete to complete)



## Quantitative Evaluation: KITTI, 3D Match



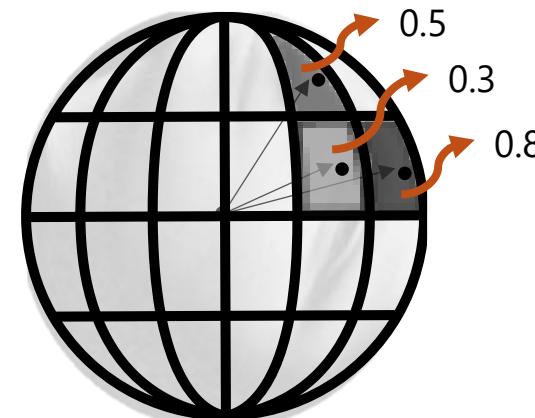
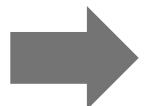
# Application 2: Spherical Image Registration

## Point Cloud Representation of Spherical Image

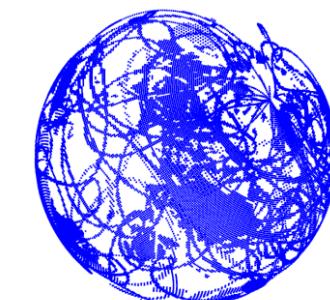
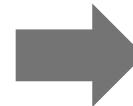
Target Spherical Image



Source Spherical Image  
(Rotated + Cluttered)



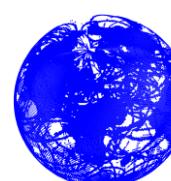
*SphImg2SphPoints*



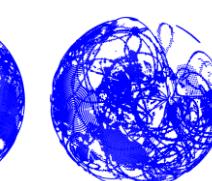
*Effect of different thresholding value*



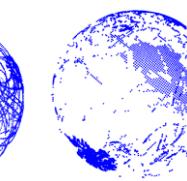
$\text{I} = 0.1$



$\text{I} = 0.2$



$\text{I} = 0.3$



$\text{I} = 0.5$

# Qualitative Evaluation: Map data



Template Spherical Image  
& 2D Projection



Rotated  
Source Sph. Image



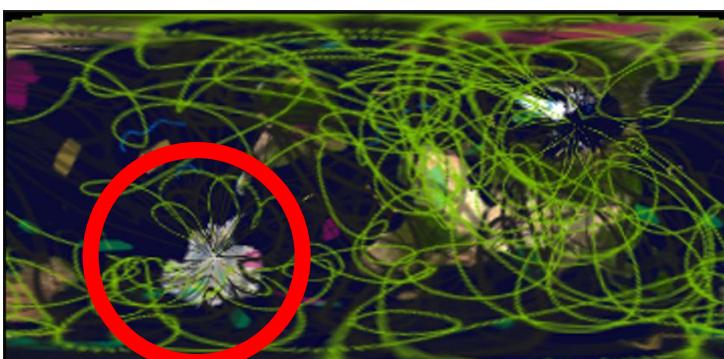
Source 2D Projection



2D projection after registration



Rotated + Noisy  
Source Sph. image



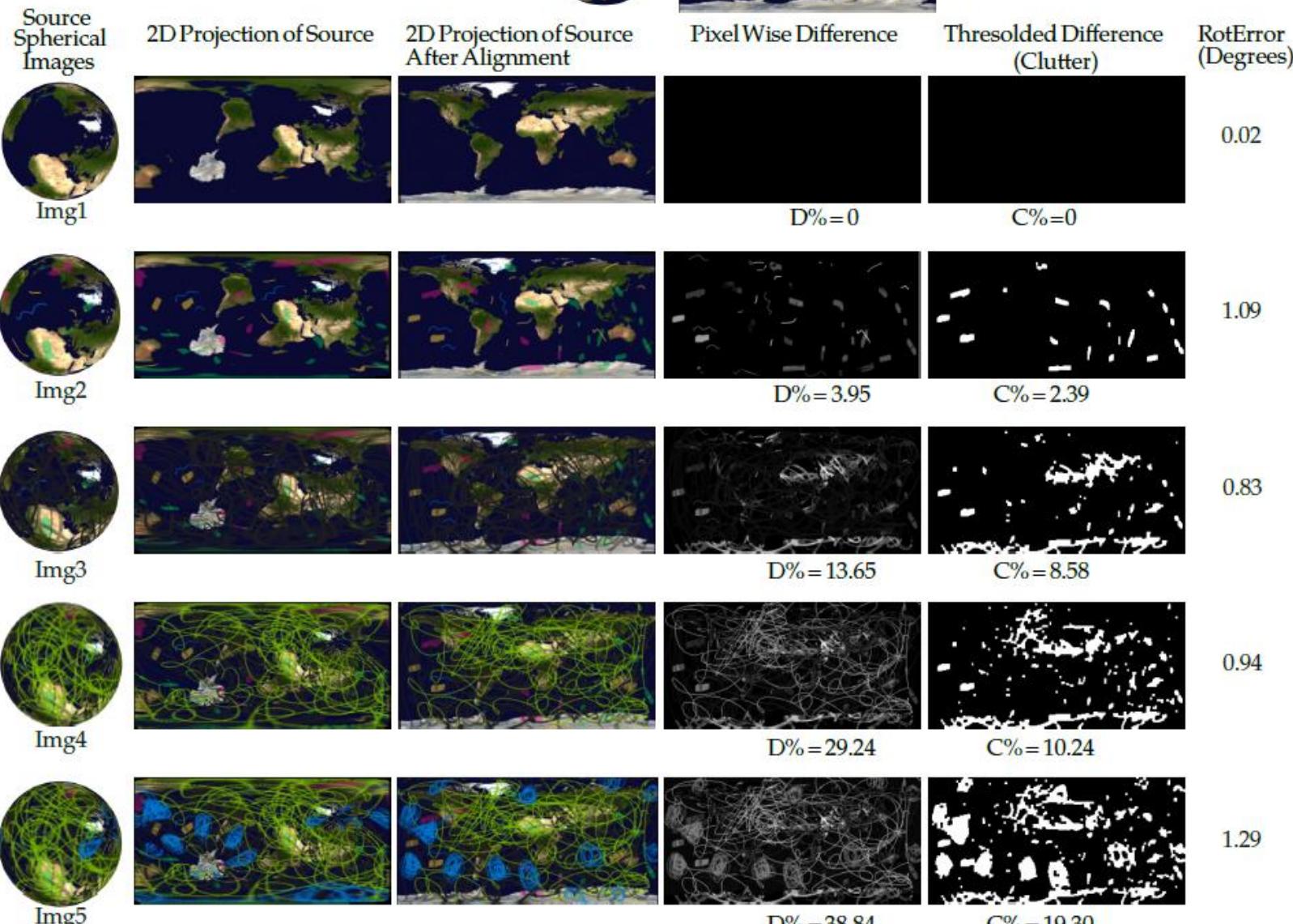
# Evaluation: Map Data

Our Method

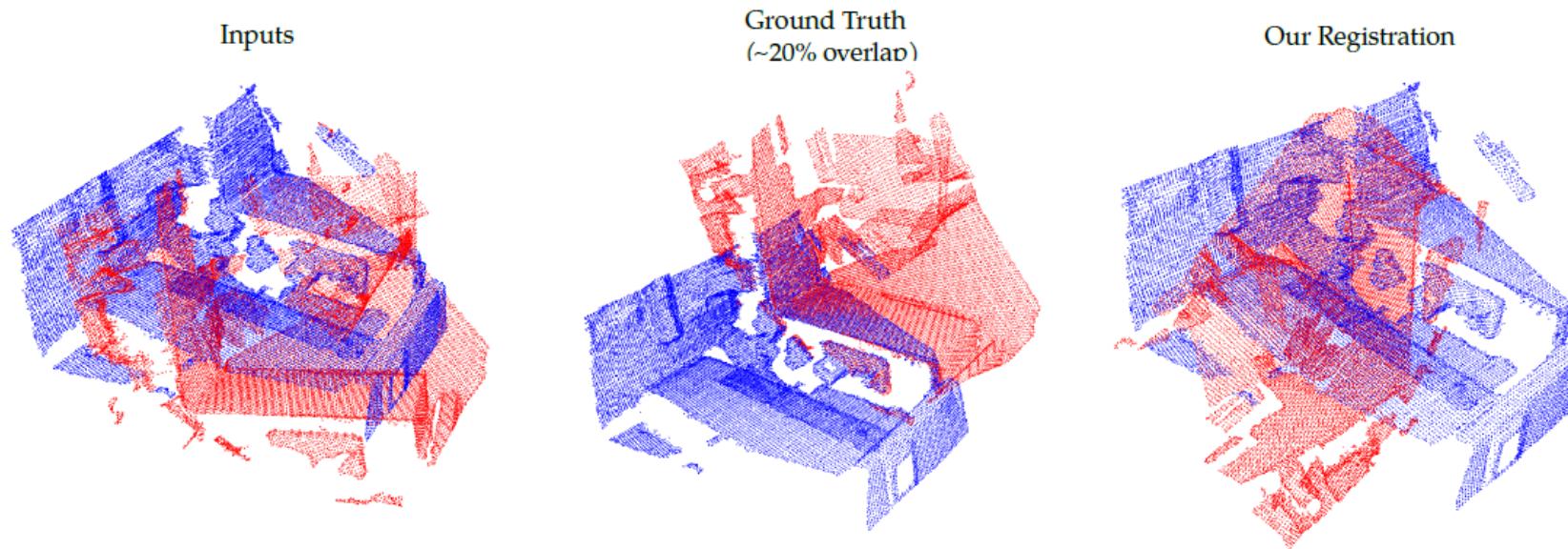
Clutter = 19%

	Rotation (deg)	Error (deg)
Alpha	55.27	0.20
Beta	12.11	0.21
Gamma	11.02	1.26

Template Spherical Image  
& 2D Projection



# Limitation and Future Work



Point cloud registration depends on the quality of spherical embedding.

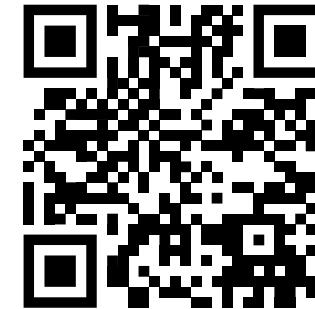
For partial clouds, rotation-invariant embeddings like EGI can be challenging, often requiring >65% overlap for partial-to-partial registration.

A future direction of this work is to improve rotation-invariant spherical embeddings for partial point clouds

# Summary

- We introduce two novel algorithms for spherical point- pattern registration, along with a third hybrid algorithm that combines the two.
- Our algorithm runs  $\sim O(n)$  time complexity.
- We demonstrate the adaptability of our algorithms for point cloud registration. Additionally, we present the Centroid Aware Spherical Embedding (CASE) method, to convert a point cloud into spherical pattern.
- We propose a novel approach for converting spherical images to spherical point clouds, enabling tasks such as rotation estimation between two spherical images.
- We present the publicly available “Robust Vector Alignment Dataset,” this can be used for evaluation of algorithms vector set alignment, spherical pattern alignment, Wahaab problem etc.

Thanks for watching



*Webpage*



*Dataset  
& Code*