

# **Symmetry and Orbit Detection via Lie-Algebra Voting**

**Project of Nuages de Points et Modélisation 3D**

---

Tong ZHAO



# **Overview**

**Introduction**

**Algorithm**

**Experiment**

**Conclusion**



# Task

Symmetries and orbits are everywhere in our daily life.



# Task

Symmetries and orbits are everywhere in our daily life.



How to find them from a raw point cloud?



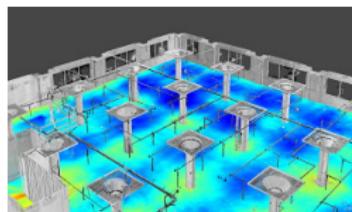
## Motivation

- Simplify the structure of the point cloud
- Eliminate noise
- Make the model physically balanced

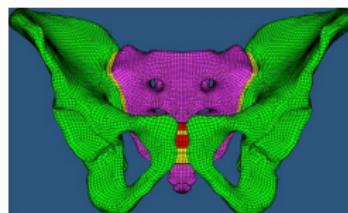


# Motivation

- Simplify the structure of the point cloud
- Eliminate noise
- Make the model physically balanced



Architecture Design



Biomedical Analysis



Physical Modelling



## Goal

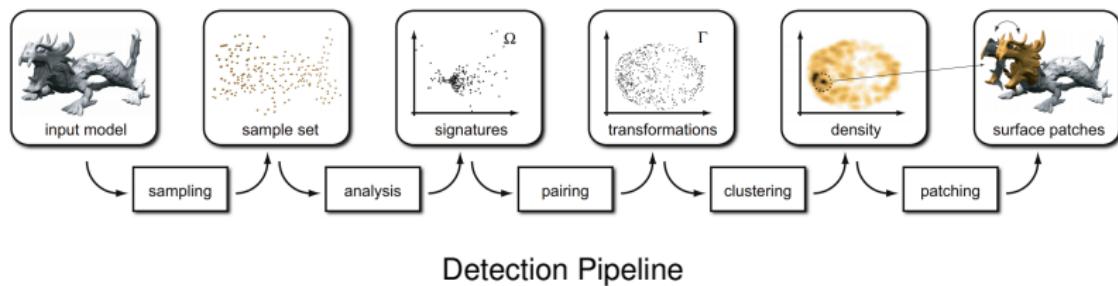
In this project, we studied the article: Symmetry and Orbit Detection via Lie-Algebra Voting [5].

- 2D Implementation in Python - Good visualization
- Parameter study in 2D cases
- 3D Implementation in C++ - Fast calculation (partially completed)
- Critical judgement



# Pipeline

The algorithm is based on a complicated pipeline [4] going from local features to partial and global features.



## Step 1: Sampling

We sample uniformly  $n$  points (no more than 500) from the raw point cloud  $P_0$ . The reduced point set  $P$  is then used for calculating local features.

Motivation: Reduce the following computational complexity



## Step 1: Sampling

We sample uniformly  $n$  points (no more than 500) from the raw point cloud  $P_0$ . The reduced point set  $P$  is then used for calculating local features.

Motivation: Reduce the following computational complexity

Limit: UNIFORMLY sampling



## Step 2: Local Feature Computation

We estimate the oriented normals and the principal curvatures for every point  $p$  in  $P$ .

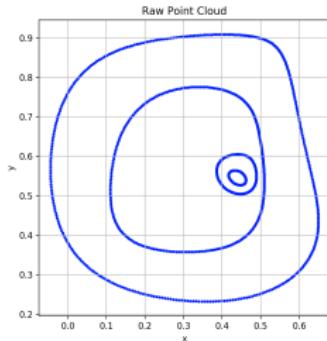
- Normal: estimated the normal  $n_i$  for each point  $p_i \in P$  by local PCA.
- Orientation: oriented by connectivity in 2D point sets, by MST in 3D point sets.
- Curvature: estimated by second order differential form.



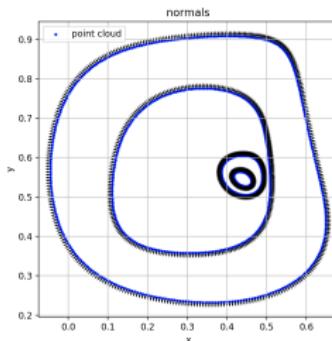
## Step 2: Local Feature Computation

We estimate the oriented normals and the principal curvatures for every point  $p$  in  $P$ .

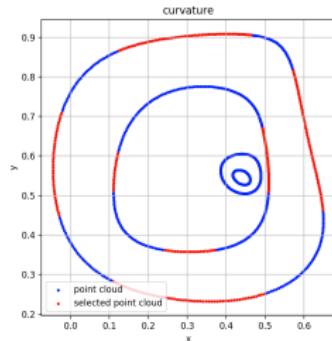
- Normal: estimated the normal  $n_i$  for each point  $p_i \in P$  by local PCA.
- Orientation: oriented by connectivity in 2D point sets, by MST in 3D point sets.
- Curvature: estimated by second order differential form.



Sampled Point Cloud  $P$



Oriented Normals

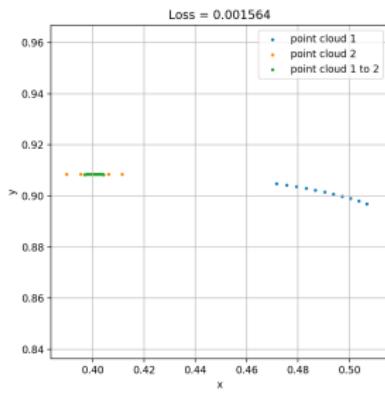


Curvatures  $> 3$

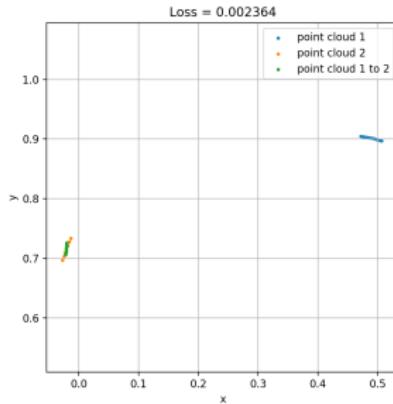


## Step 3: Point Pairing

We sample randomly one-fifth points from  $P$ , noted  $\tilde{P}$ . Then for each pair of points  $(p_i, p_j)$  where  $p_i \in \tilde{P}$ ,  $p_j \in P$ , we estimate a transformation  $T_{ij}$ . Transformations with large alignment error are rejected, given a threshold  $s_1$ .



Accepted Example



Rejected Example



## Step 4: Clustering

Given  $T_{ij}$  in  $\text{SIM}(2)$  /  $\text{SIM}(3)$ , we embed it in the corresponding Lie algebra space  $\mathfrak{sim}(2)$  /  $\mathfrak{sim}(3)$  [2].

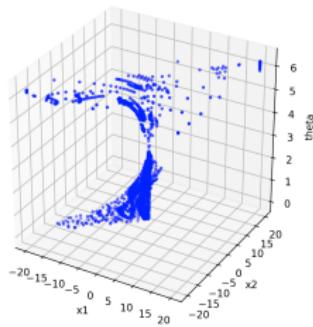
$$T = \begin{pmatrix} R & t \\ 0 & w^{-1} \end{pmatrix} \rightarrow \log(T) = \begin{pmatrix} \omega & u \\ 0 & -s \end{pmatrix}$$

Since  $\omega$  is a skew-symmetric matrix, the embedding can be represented by a vector:

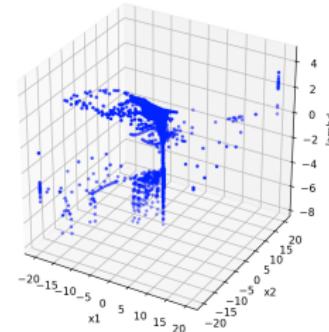
- 2D cases:  $\log(T) \in \mathbb{R}^4$
- 3D cases:  $\log(T) \in \mathbb{R}^7$



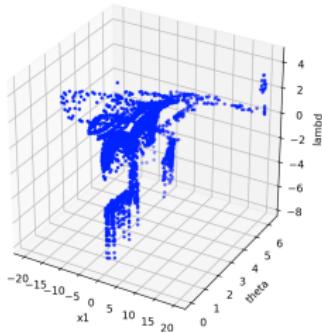
## Step 4: Clustering



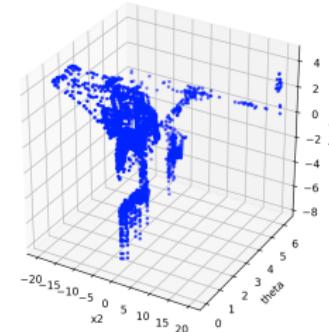
$(x_1, x_2, \theta)$



$(x_1, x_2, \lambda)$



$(x_1, \theta, \lambda)$



$(x_2, \theta, \lambda)$



## Step 4: Distance Metric

Given two transformations  $F$  and  $G$ , we have  $\delta = FG^{-1}$  use a metric as following:

$$d^2(F, G) = \log(\delta)^t \begin{pmatrix} \alpha Id & 0 & 0 \\ 0 & \beta Id & 0 \\ 0 & 0 & \gamma \end{pmatrix} \log(\delta) = \|\log(\delta)\|_E^2 = \|\log(F) - \log(G)\|_E^2$$



## Step 4: Distance Metric

Given two transformations  $F$  and  $G$ , we have  $\delta = FG^{-1}$  use a metric as following:

$$d^2(F, G) = \log(\delta)^t \begin{pmatrix} \alpha Id & 0 & 0 \\ 0 & \beta Id & 0 \\ 0 & 0 & \gamma \end{pmatrix} \log(\delta) = \|\log(\delta)\|_E^2 = \|\log(F) - \log(G)\|_E^2$$

This distance is not independent from its scale.



## Step 4: Detection

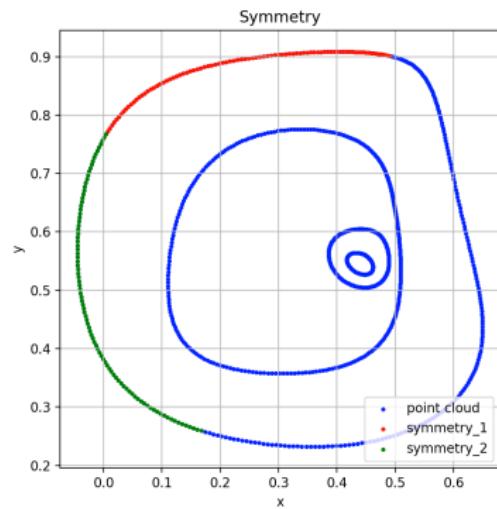
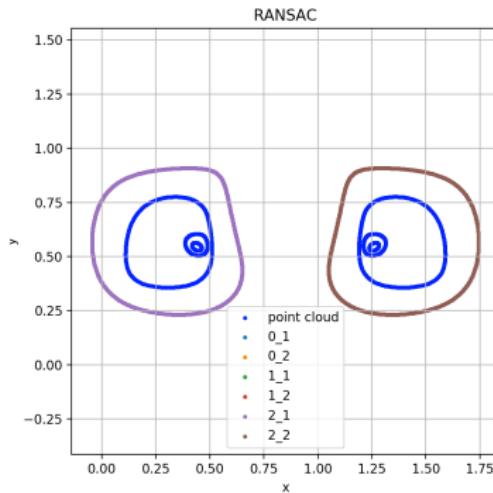
- Symmetry Detection - Mean Shift [3]: The symmetry is represented by the mode of the transformations.
- Orbit Detection - RANSAC: According to Lie Algebra properties, a k-orbit always generates a k-dimensional linear subspace.

Both algorithms are implemented in Lie Algebra domain using the defined metric.



## Step 5: Patching

Given a transformation  $T_{ij}$ , we perform a Region Growing algorithm [1] on both  $p_i$  and  $p_j$  to find the corresponding patches.

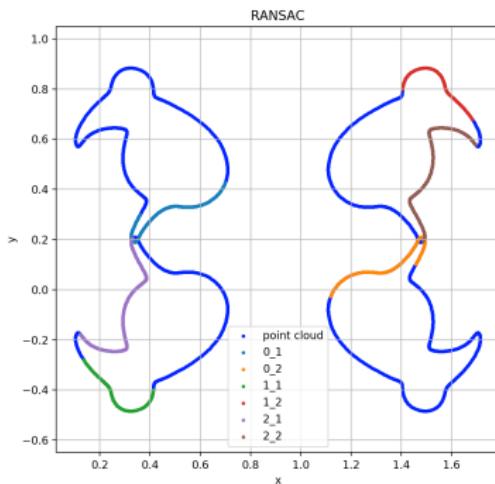


RANSAC

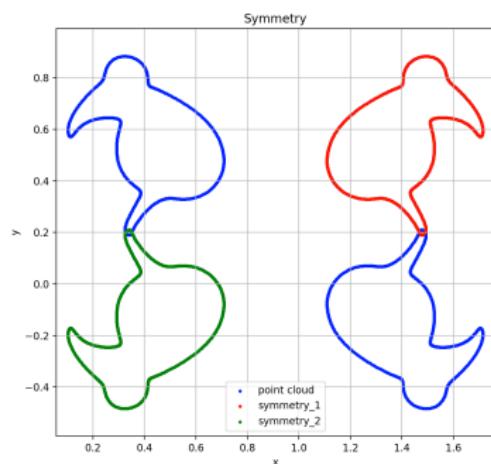
Mean Shift



## Example 1: Bird



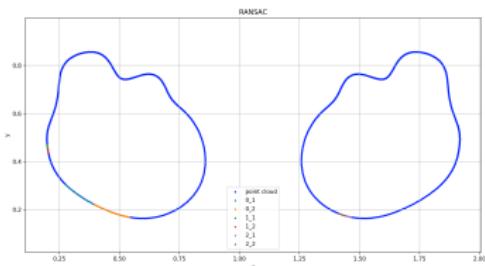
Orbit Detection - Bird



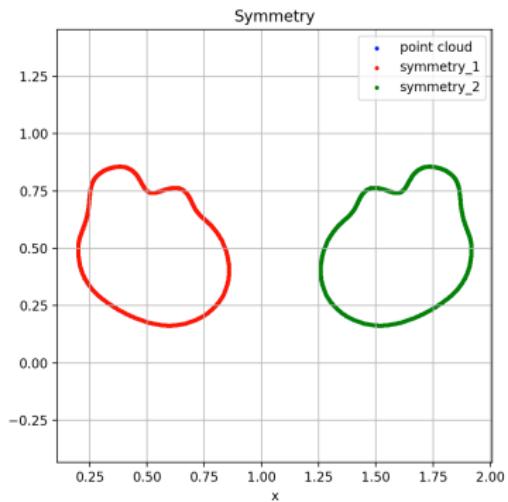
Symmetry Detection - Bird



## Example 2: Blob



Orbit Detection - Blob



Symmetry Detection - Blob



# Parameter Tuning

Parameter	Role	Choice
<b>Radius <math>r</math></b>	decides the quality of estimations	can be estimated by average spacing
<b>Number of points <math>n</math></b>	trade-off between accuracy and complexity	between 100 and 500
<b>Threshold for pairing <math>s_1</math></b>	controls the quality of the paired transformations	fixed to 0.0005
<b>Threshold for RANSAC <math>s_2</math></b>	decides the quality of RANSAC	fixed to 0.005
<b>Variance of gaussian kernel <math>\sigma</math></b>	decides the smoothness of the gram matrix in Mean-shift	can be estimated by Monte-Carlo method
<b>Threshold for region growing <math>s_3</math></b>	controls the quality of the matching patches	difficult to decide



## Advantage

- 1. An Unified Framework** to detect both local and global symmetries and orbits. It avoids mapping the transformations to humain-designed spaces based on which symmetries are looked for.
- 2. A Coordinate Frame Independent Clustering** to reduce manual tuning everytime when we change the point cloud.



## Disadvantage

- 1. High Computational Cost** due to the huge amount of possible transformations. A small amount of points lead to a bad result since it can not represent perfectly the raw shape.
- 2. Parameter Tuning** is important to get a good result but it is not trivial.
- 3. Limited Sampling Method** leads to failure in some cases.
- 4. Subjective Evaluation Criteria** makes it difficult to evaluate the algorithm quantitatively.



## Future works

- 1. Transformations based on segmentation** can help us to reduce the complexity of the algorithm and make it more robust.
- 2. Deep learning methods** may help to capture symmetries and orbits given the transformations.



## References

- [1] Rolf Adams and Leanne Bischof. Seeded region growing. *IEEE Transactions on pattern analysis and machine intelligence*, 16(6):641–647, 1994.
- [2] Jose-Luis Blanco. A tutorial on se (3) transformation parameterizations and on-manifold optimization. *University of Malaga, Tech. Rep*, 3, 2010.
- [3] Yizong Cheng. Mean shift, mode seeking, and clustering. *IEEE transactions on pattern analysis and machine intelligence*, 17(8):790–799, 1995.
- [4] Niloy J Mitra, Leonidas J Guibas, and Mark Pauly. Partial and approximate symmetry detection for 3d geometry. In *ACM Transactions on Graphics (TOG)*, volume 25, pages 560–568. ACM, 2006.
- [5] Zeyun Shi, Pierre Alliez, Mathieu Desbrun, Hujun Bao, and Jin Huang. Symmetry and orbit detection via lie-algebra voting. In *Computer Graphics Forum*, volume 35, pages 217–227. Wiley Online Library, 2016.

