

# Ransac

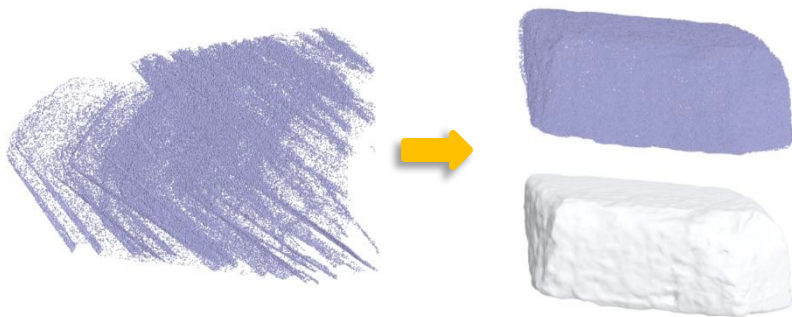


Paolo Cignoni

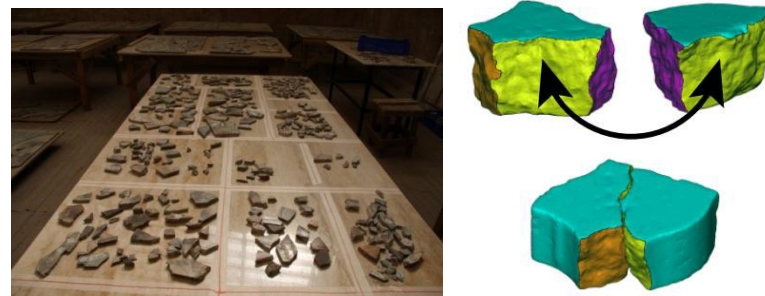


3D GEOMETRIC MODELING & PROCESSING

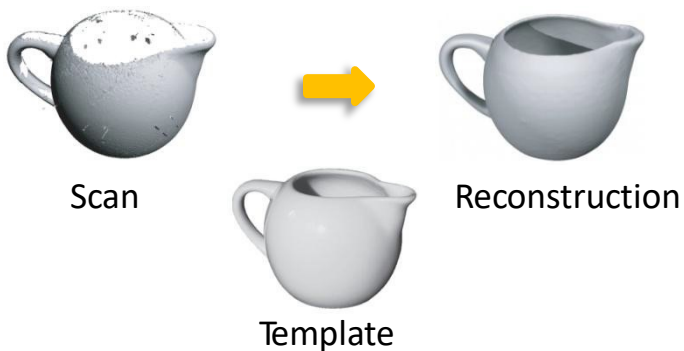
# Applications



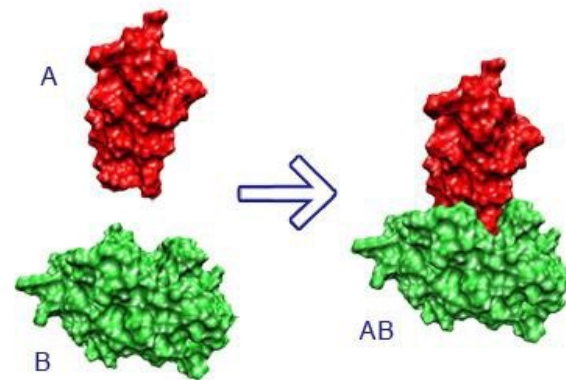
Surface reconstruction



Fragment assembly

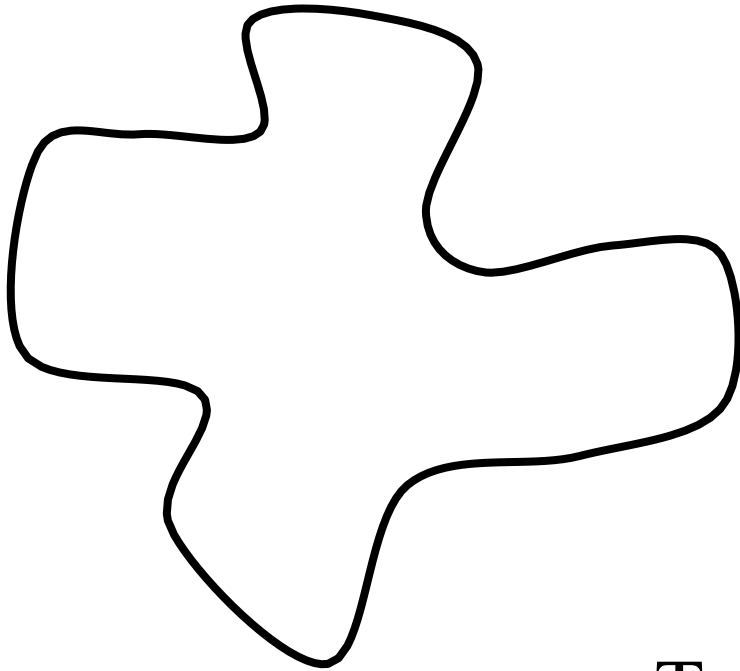


Object completion



Protein docking

# Rigid Matching

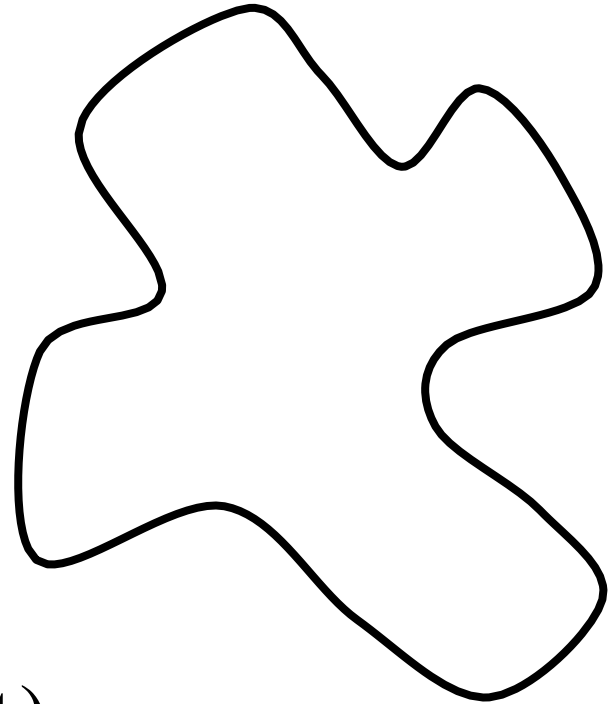


$S_1$

$$T = (R; t)$$



*Rotation and translation*

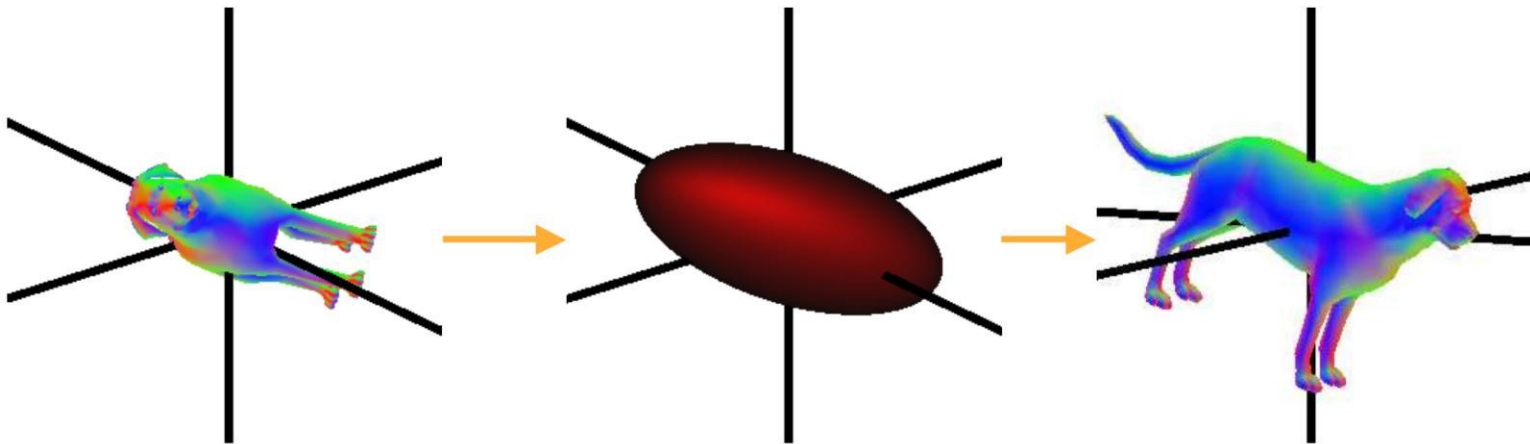


# Approach --- PCA

- Use PCA to place models into a canonical coordinate frame

Covariance  
matrix computation

Principal Axis  
alignment



# Principal Axis Computation

- Given a collection of points  $\{\mathbf{p}_i\}$ , form the co-variance matrix:

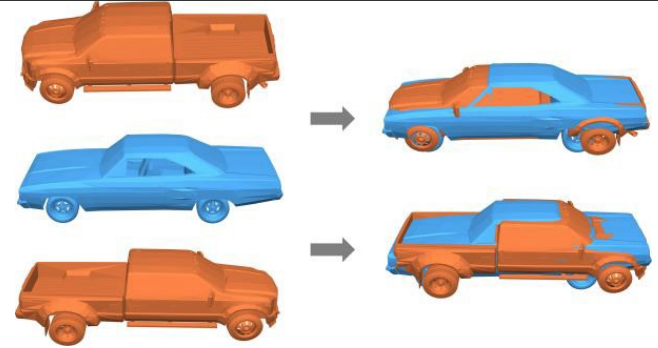
$$\mathbf{c} = \frac{1}{N} \sum_{i=1}^N \mathbf{p}_i$$

$$C = \frac{1}{N} \sum_{i=1}^N \mathbf{p}_i \mathbf{p}_i^T - \mathbf{c} \mathbf{c}^T$$

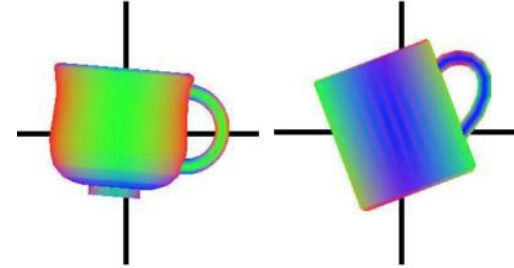
- Compute eigenvectors of matrix  $C$

# Issues with PCA

- Principal axes are not oriented



- Axes are unstable when principal values are similar



- Partial similarity

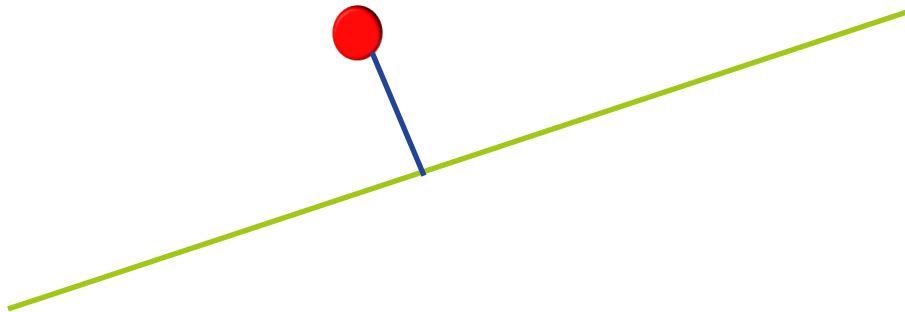
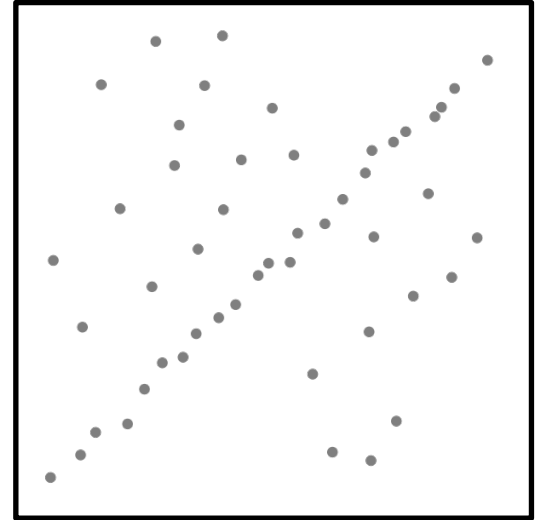


# Ransac: Basis

- **R**andom **S**ample **C**onsensus
  - Hypothesize and test.
  
- Used for Parametric Matching
  - Want to match two things.
  - Hypothesized match can be described by parameters (eg., translation, affine.)
  
- Match enough features to determine a hypothesis.
  - See if it is good.
  - Repeat.

# Ransac Example

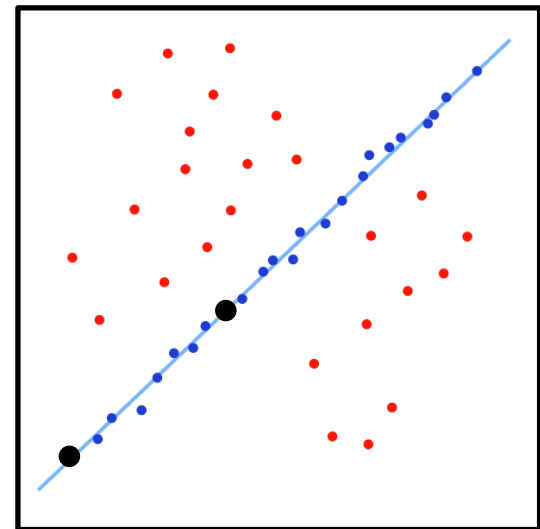
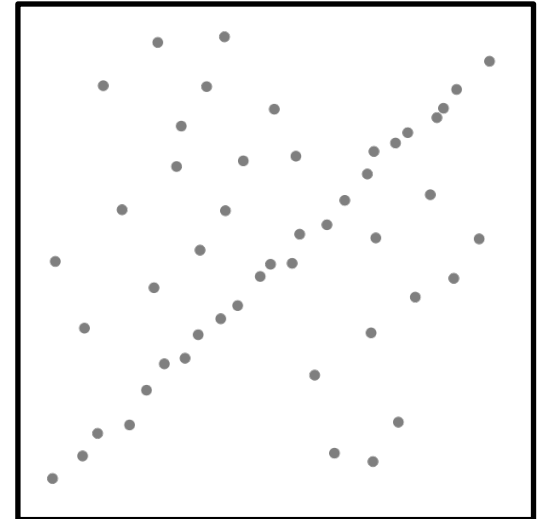
- Grouping Points into Lines
- Basic Info on lines





# Ransac

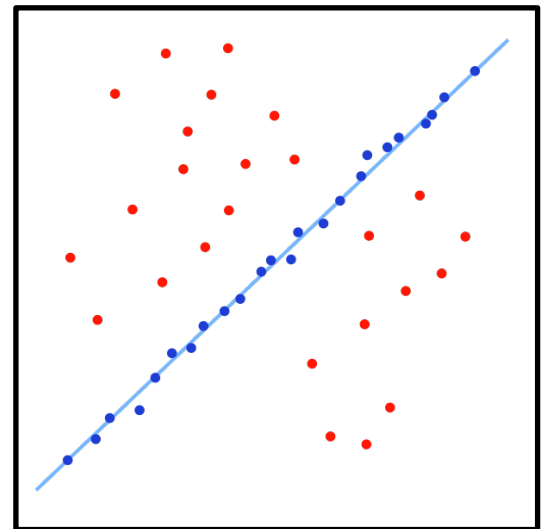
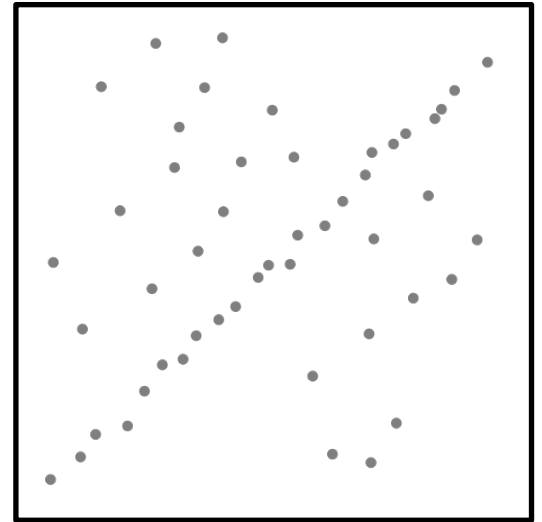
- Select a random subset of the original data. Call this subset the hypothetical inliers.
- A model is fitted to the set of hypothetical inliers.
- All other data are then tested against the fitted model.
- The estimated model is reasonably good if sufficiently many points have been classified as part of the consensus set.
- Afterwards, the model may be improved by re-estimating it using all members of the consensus set.



# Ransac

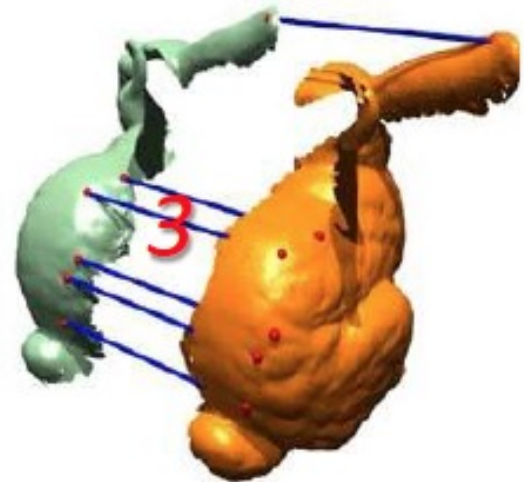
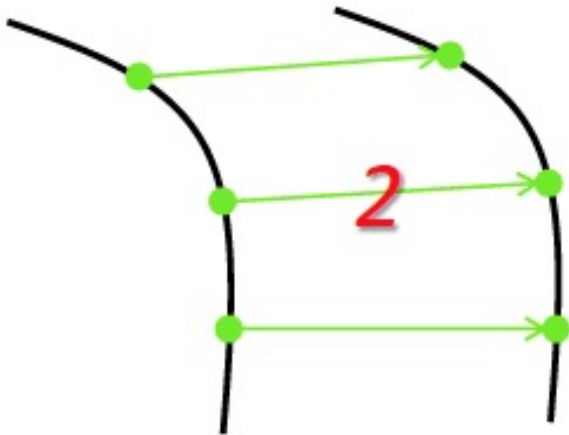
- Complexity?
- How many samples?
  - $p$  is fraction of points on the line.
    - Fraction of inlayer/total
  - $n$  points needed to define hypothesis (2 for lines)
  - $k$  number of trials.
- Probability that after  $N$  trials I've the correct solution is:

$$1-(1-p^n)^N$$



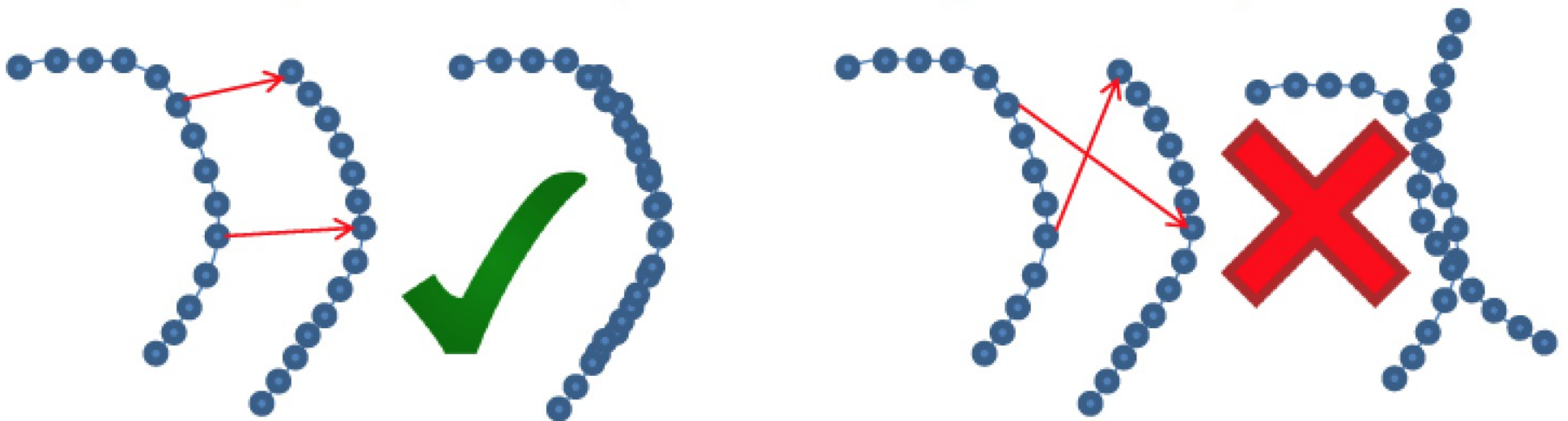
# Ransac

- How many point-pairs specify a rigid transform?
  - In  $R^2$ ?
  - In  $R^3$ ?
- Additional constraints?
  - Distance preserving
  - Stability?



# Ransac

- Preprocessing: sample each object
- Iterate
  - Step I: Sample three (two) pairs, check distance constraints
  - Step II: Fit a rigid transform
  - Step III: Check how many point pairs agree. If above threshold, terminates; otherwise goes to Step I

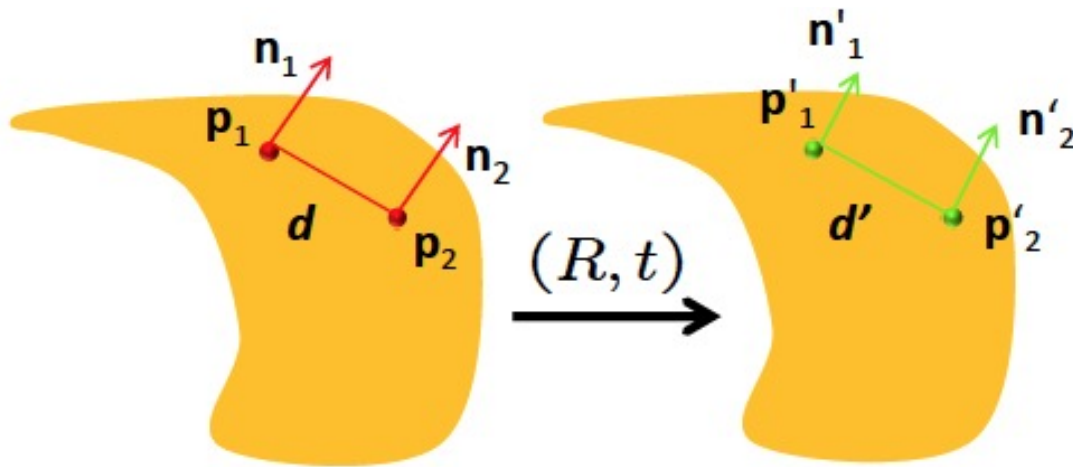


# Ransac

- Sampling
  - Feature point detection
- Correspondences
  - Use feature descriptors
  - Denote a larger success rate  $p$
  - Probability a descriptor identifies the correct match
  - Try only candidates made by pair of samples with similar descriptor.
- Basic analysis
  - The probability of having a valid triplet  $p^3$
  - The probability of having a valid triplet in  $N$  trials is  $1-(1-p^3)^N$

# Ransac +

- How many surfel (position + normal) correspondences specify a rigid transform?



Constraints:

- $\|p_1 - p_2\| \approx \|p'_1 - p'_2\|$
- $\angle(n_1, d) = \angle(n'_1, d')$
- $\angle(n_2, d) = \angle(n'_2, d')$
- $\angle(n_1, n_2) = \angle(n'_1, n'_2)$

- Reduce the number of trials from  $O(m^3)$  to  $O(m^2)$

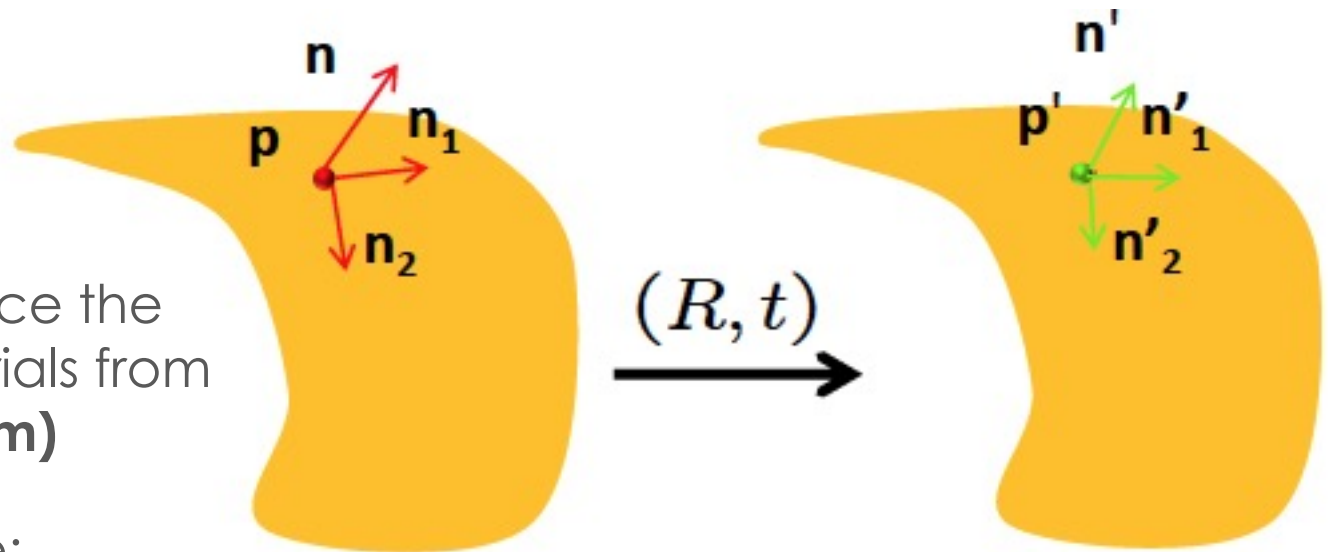
$$t = \frac{p'_1 + p'_2}{2} - \frac{p_1 + p_2}{2}$$

- Success rate:  $1 - (1 - p^2)^N$

$$[n_1, n_2, d] \xrightarrow{R} [n'_1, n'_2, d']$$

# Ransac ++

- How many frame correspondences specify a rigid transform?
  - Principal curvatures
  - Local PCA



- Further reduce the number of trials from  $O(m^2)$  to  $O(m)$

- Success rate:  
 $1 - (1 - p)^N$

$$t = p' - p$$

$$R(n, n_1, n_2) \approx (n', n'_1, n'_2)$$

# Post Processing

- ▣ Refine the match via ICP



Input



After matching



After registration