

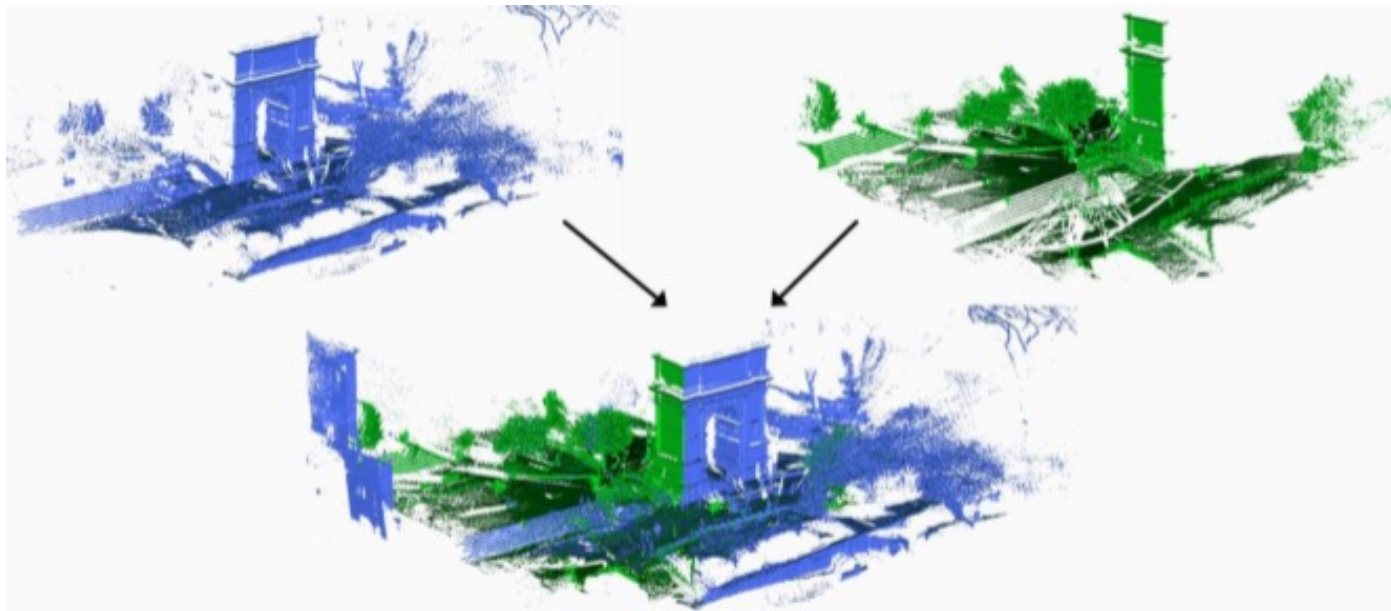


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Geometry Registration

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什么是注册？



- 计算最佳空间变换，以使得多个几何曲面之间进行对齐。
 - 将传感器采集的多个局部测量数据拼接成一个完整的几何模型
 - 将新测量数据对齐到已知模型以估计其姿态

变换类型

- Same object in a different position: size and shape preserving
 - Rigid-body transformation (rotation and translation)
 - Six degrees of freedom

◆ translation $\mathbf{t} = (t_x, t_y, t_z)^T$

◆ rotation (α, β, γ)

$$\mathbf{T}_{\text{rigid}}(\mathbf{x}) = \mathbf{R}\mathbf{x} + \mathbf{t}$$

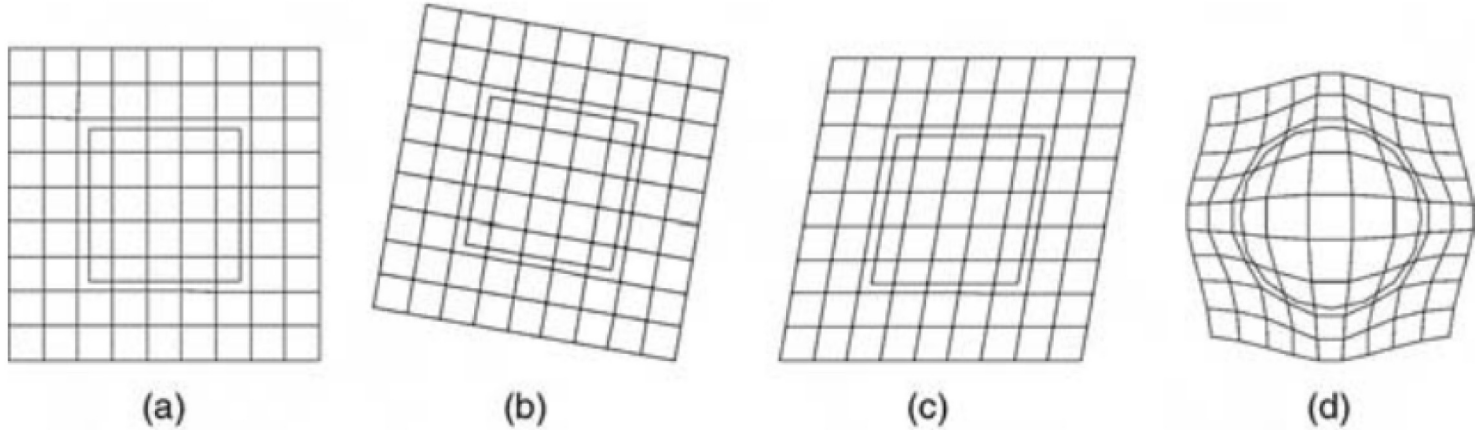
$$\mathbf{T}_{\text{rigid}}(\mathbf{x}) = \begin{bmatrix} \cos \beta \cos \gamma & \cos \alpha \sin \gamma + \sin \alpha \sin \beta \cos \gamma & \sin \alpha \sin \gamma - \cos \alpha \sin \beta \cos \gamma & t_x \\ -\cos \beta \sin \gamma & \cos \alpha \cos \gamma - \sin \alpha \sin \beta \sin \gamma & \sin \alpha \cos \gamma + \cos \alpha \sin \beta \sin \gamma & t_y \\ \sin \beta & -\sin \alpha \cos \beta & \cos \alpha \cos \beta & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$

变换类型

- Affine or Linear Transformation
 - Rigid-body transformation (rotation and translation)
 - Scaling and Shearing
 - Twelve degrees of freedom

$$\mathbf{T}(\mathbf{x}) = \begin{bmatrix} a_{00} & a_{01} & a_{02} & a_{03} \\ a_{10} & a_{11} & a_{12} & a_{13} \\ a_{20} & a_{21} & a_{22} & a_{23} \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$

变换类型



Example of different types of transformations of a square

(a) identity transformation

(c) affine transformation

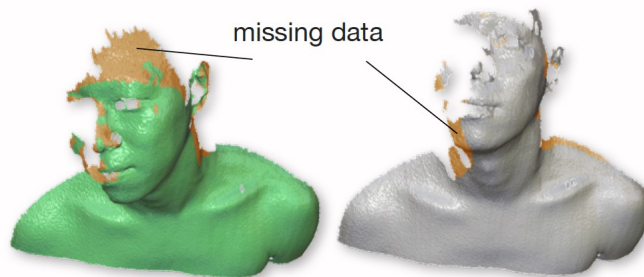
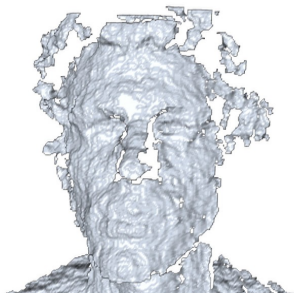
(b) rigid transformation

(d) nonrigid transformation

配准问题中的一些挑战



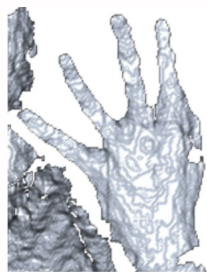
Noise



Partial matching



Ambiguity



Illumination changes

配准问题建模

- 将配准问题表达为能量最小化问题：

$$\operatorname{argmax}_T E_{reg}(T, P, Q)$$

$$E_{reg}(T, P, Q) = E_{match}(T, P, Q) + E_{prior}(T)$$

配准误差

如何衡量配准结果的质量？

变换误差

变换的类型与表示方式？

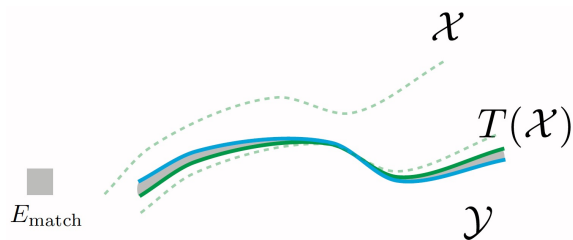
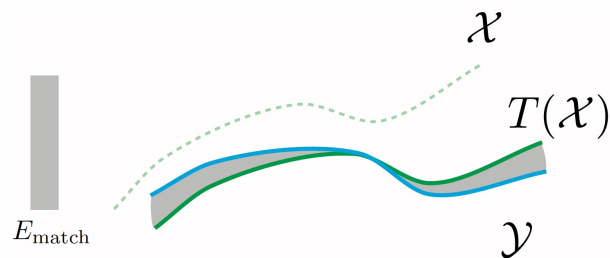
配准问题建模

- 配准误差

$$E_{reg}(T, P, Q) = E_{match}(T, P, Q) + E_{prior}(T)$$

$$E_{match}(T, P, Q) = \int_{\mathcal{X}} \phi(T(p), Q) dx$$

距离度量函数



配准问题建模

- 变换误差

$$E_{ren}(T, P, Q) = E_{match}(T, P, Q) + E_{prior}(T)$$



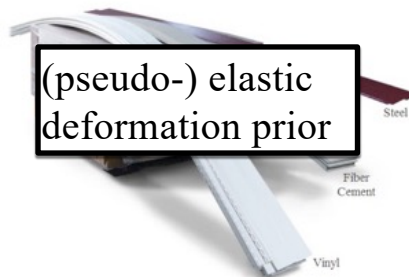
rigid motion
prior

Rigid



skeletal
model prior

Articulated



(pseudo-) elastic
deformation prior

Elastic



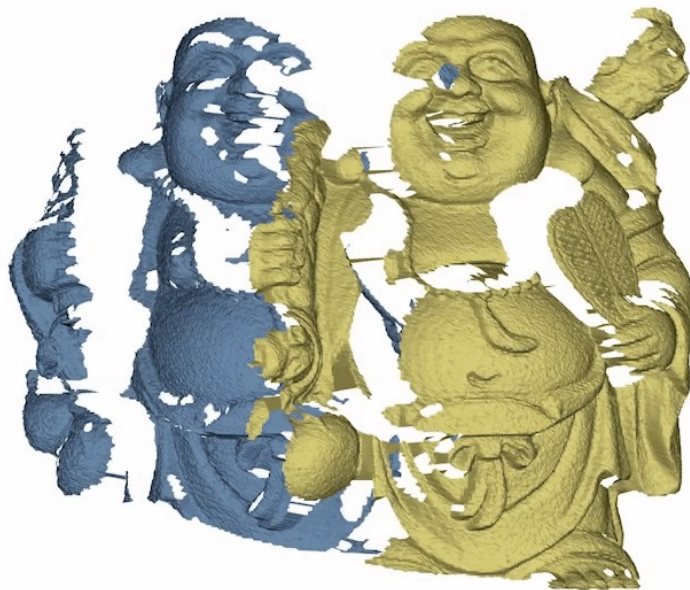
data-driven
prior

Composite

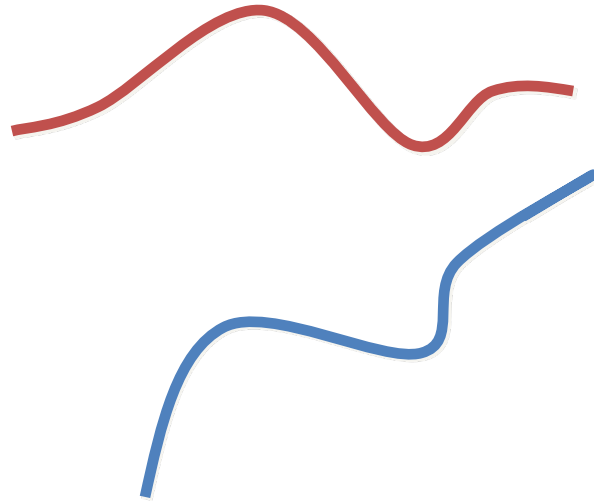
几何数据融合与跟踪-刚性注册

- 刚体几何建模：将不同视角点云进行刚性拼接，以获得完整几何模型

$$E(\mathbf{T}) = \sum_{(\mathbf{p}, \mathbf{q}) \in K} \|\mathbf{p} - \mathbf{T}\mathbf{q}\|^2 \quad \mathbf{T} \text{ 是一个包含旋转与平移的刚性变换}$$



Aligning 3D Data

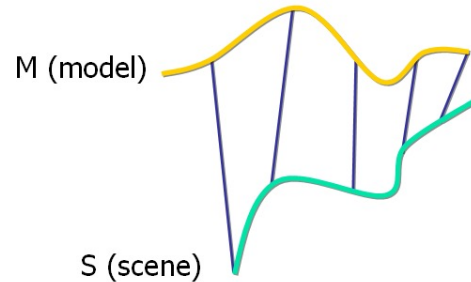


Corresponding Point Set Alignment

- Let M be a model point set.
- Let S be a scene point set.

We assume:

1. $N_M = N_S$.
2. Each point S_i correspond to



Corresponding Point Set Alignment

The MSE objective function :

$$f(R, T) = \frac{1}{N_S} \sum_{i=1}^{N_S} \|m_i - Rot(s_i) - Trans\|^2$$

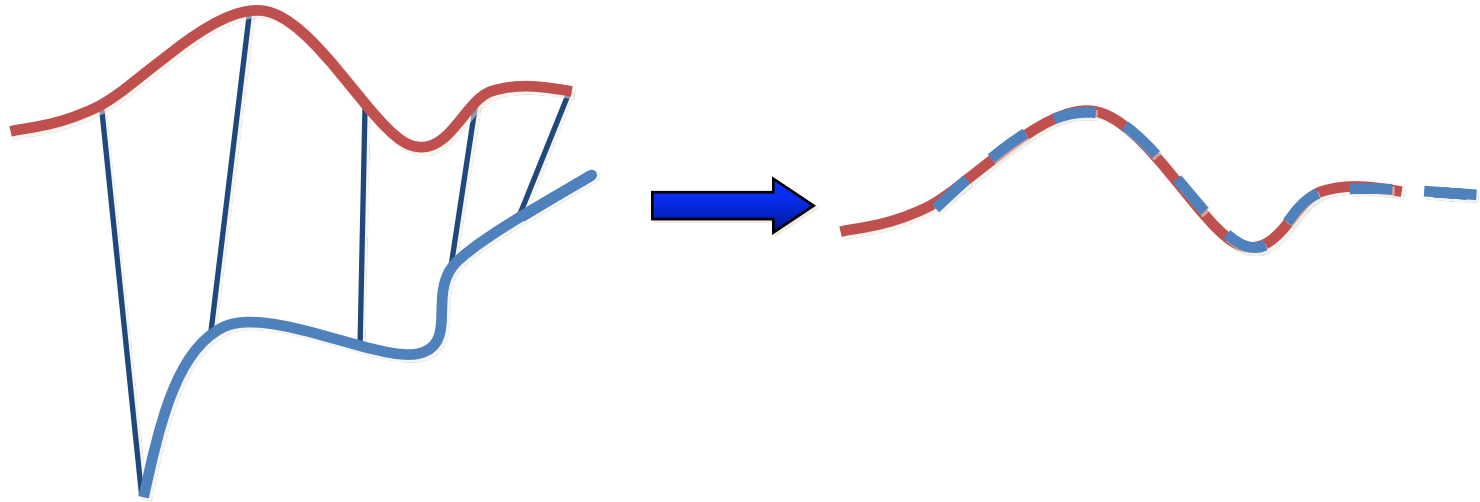
$$f(q) = \frac{1}{N_S} \sum_{i=1}^{N_S} \|m_i - R(q_R)s_i - q_T\|^2$$

The alignment is:

$$(rot, trans, d_{mse}) = \Phi(M, S)$$

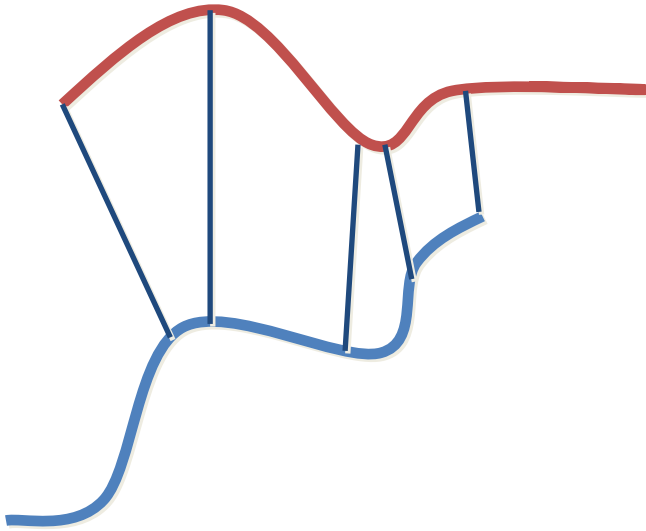
Aligning 3D Data

- If correct correspondences are known, can find correct relative rotation/translation



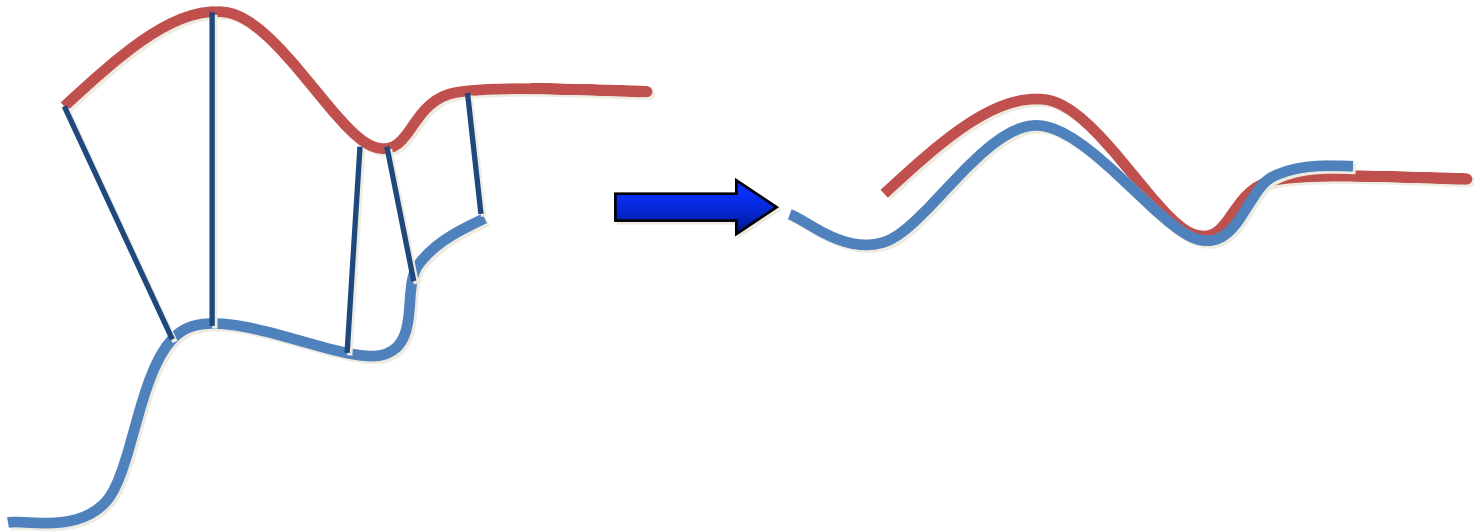
Aligning 3D Data

- How to find correspondences: User input? Feature detection? Signatures?
- Alternative: assume **closest** points correspond



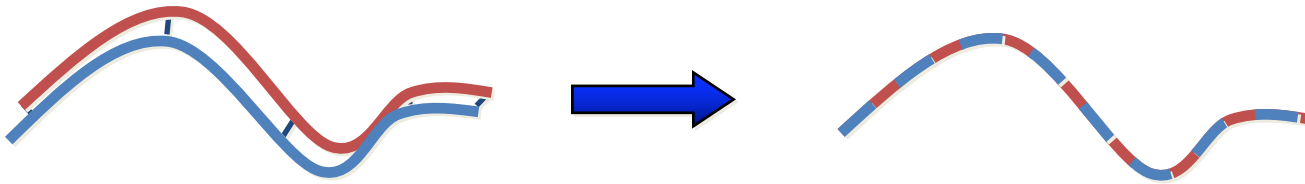
Aligning 3D Data

- How to find correspondences: User input? Feature detection? Signatures?
- Alternative: assume **closest** points correspond



Aligning 3D Data

- Converges if starting position “close enough”



Closest Point

- Given 2 points r_1 and r_2 , the Euclidean distance is:

$$d(r_1, r_2) = \|r_1 - r_2\| = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2}$$

- Given a point r_1 and set of points A , the Euclidean distance is:

$$d(r_1, A) = \min_{i \in 1..n} d(r_1, a_i)$$

Finding Matches

- The scene shape S is aligned to be in the best alignment with the model shape M .
- The distance of each point s of the scene from the model is :

$$d(s, M) = \min_{m \in M} \|m - s\|$$

Finding Matches

$$d(s, M) = \min_{m \in M} d\|m - s\| = d(s, y)$$

$$y \in M$$

$$Y = C(S, M)$$

$$Y \subseteq M$$

C – the closest point operator

Y – the set of closest points to S

Finding Matches

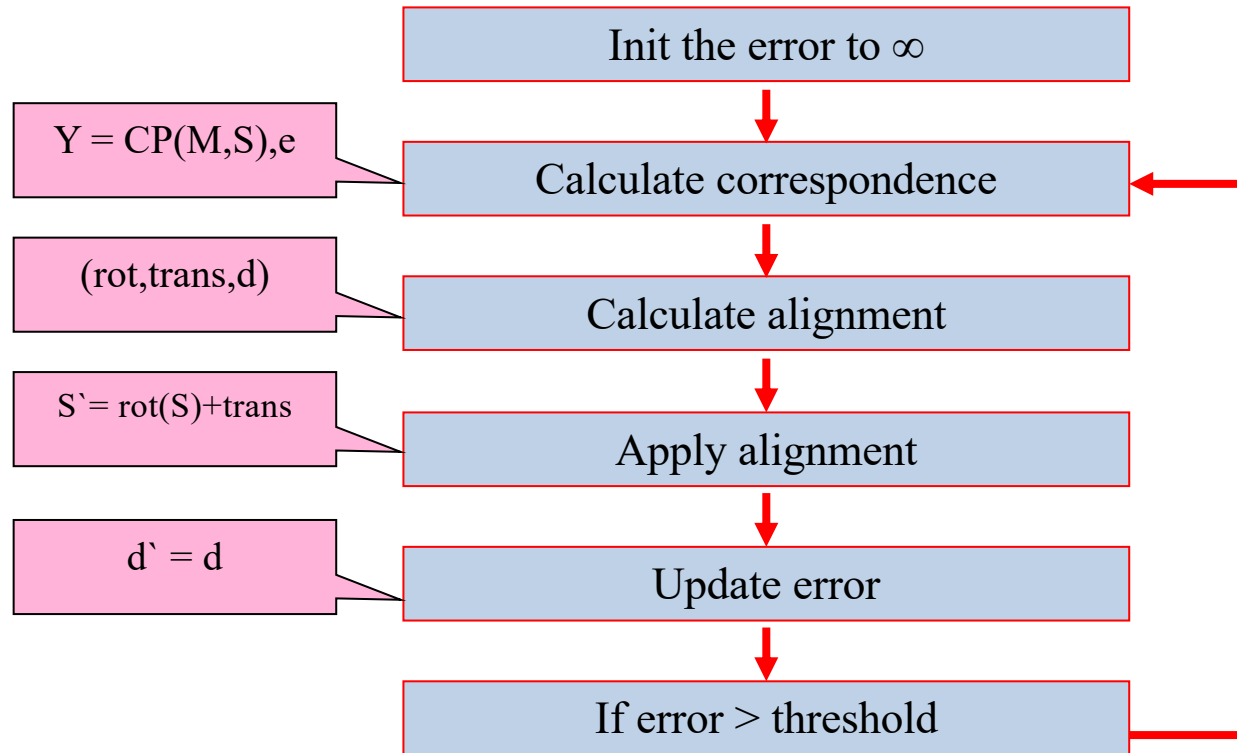
- Finding each match is performed in $O(N_M)$ worst case.
- Given Y we can calculate alignment

$$(rot, trans, d) = \Phi(S, Y)$$

- S is updated to be :

$$S_{new} = rot(S) + trans$$

The Algorithm



Convergence Theorem

- The ICP algorithm always converges monotonically to a local minimum with respect to the MSE distance objective function.

Convergence Theorem

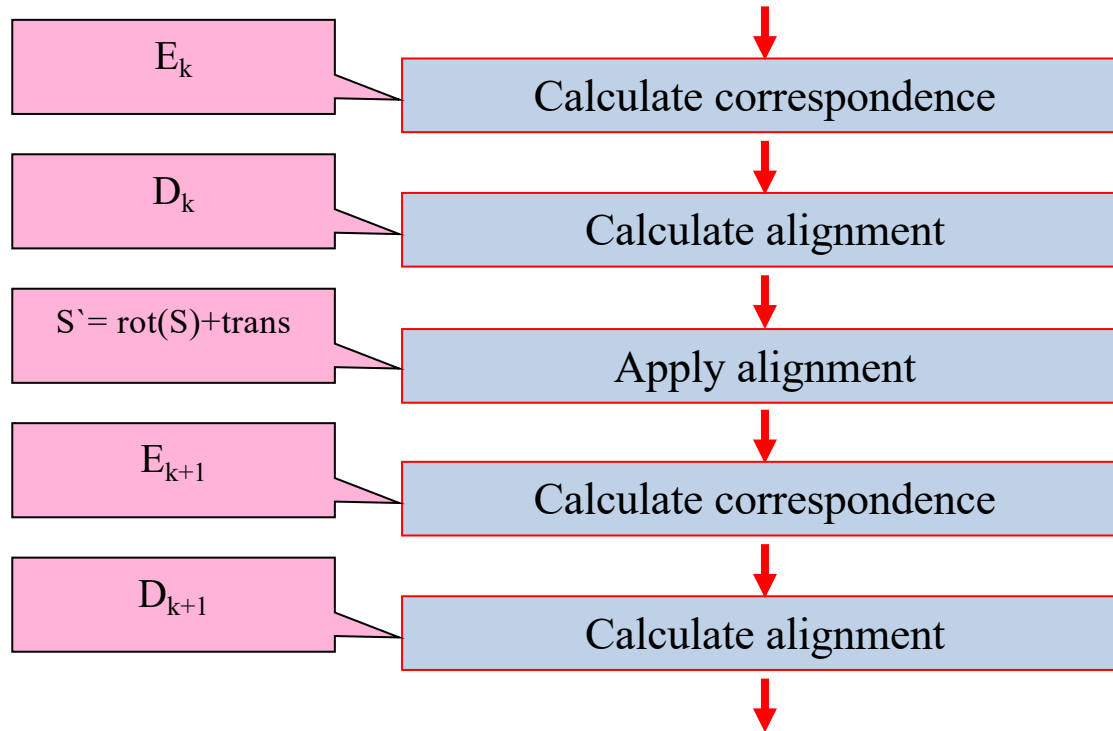
- Correspondence error :

$$e_k = \frac{1}{N_S} \sum_{i=1}^{N_S} \|y_{ik} - s_{ik}\|^2$$

- Alignment error:

$$d_k = \frac{1}{N_S} \sum_{i=1}^{N_S} \|y_{ik} - Rot_k(s_{io}) - Trans_k\|^2$$

Convergence Theorem



Convergence Theorem

- Proof :

$$S_k = Rot_k(S_0) + Trans_k$$

$$Y_k = C(M, s_k)$$

$$e_k = \frac{1}{N_S} \sum_{i=1}^{N_S} \|y_{ik} - s_{ik}\|^2$$

$$d_k = \frac{1}{N_S} \sum_{i=1}^{N_S} \|y_{ik} - Rot_k(s_{io}) - Trans_k\|^2$$

Convergence Theorem

- Proof : $d_k \leq e_k$

If not - the identity transform would yield a smaller MSE than the least square alignment.

Apply the alignment q_k on $S_0 \rightarrow S_{k+1}$.

Assuming the correspondences are maintained :
the MSE is still d_k .

$$d_k = \frac{1}{N_M} \sum_{i=1}^{N_M} \|y_{ik} - S_{ik}\|^2$$

Convergence Theorem

- Proof :

After the last alignment, the closest point operator is applied : $Y_{k+1} = C(M, S_{k+1})$

It is clear that:

$$\|y_{i,k+1} - S_{i,k+1}\| \leq \|y_{ik} - S_{i,k+1}\|$$
$$e_{k+1} \leq d_k$$

Thus : $0 \leq d_{k+1} \leq e_{k+1} \leq d_k \leq e_k$

Time analysis

Each iteration includes 3 main steps

A. Finding the closest points :

$O(N_M)$ per each point

$O(N_M * N_S)$ total.

B. Calculating the alignment: $O(N_S)$

C. Updating the scene: $O(N_S)$

Optimizing the Algorithm

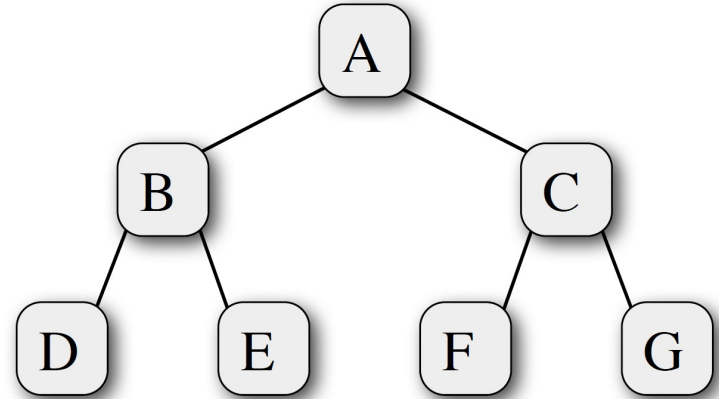
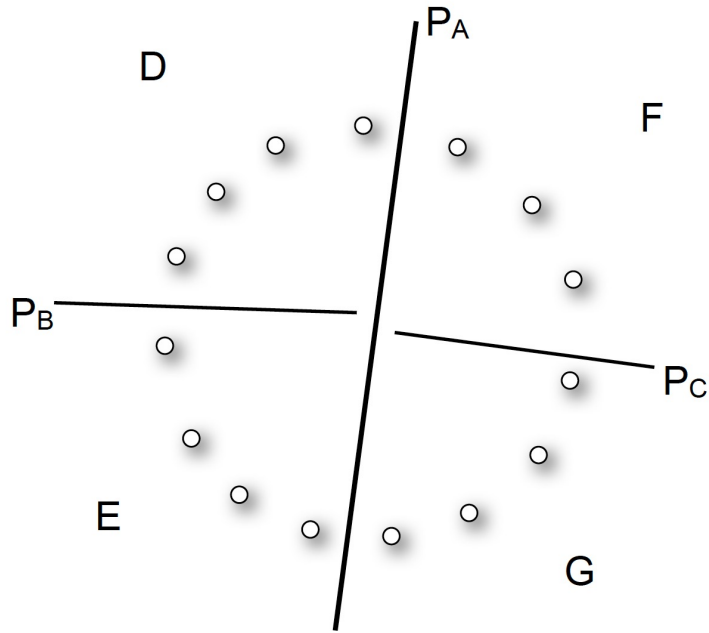
The best match/nearest neighbor problem :

Given a record, and a dissimilarity measure **D**, find the closest record from a set to the query record.

Closest Point Search

- Find closest point of a query point
 - Brute force: $O(n)$ complexity
- Use hierarchical BSP tree
 - Binary space partitioning tree (also kD-tree)
 - Recursively partition 3D space by planes
 - Tree should be balanced, put plane at median
 - $\log(n)$ tree levels, complexity $O(\log n)$

BSP Closest Point

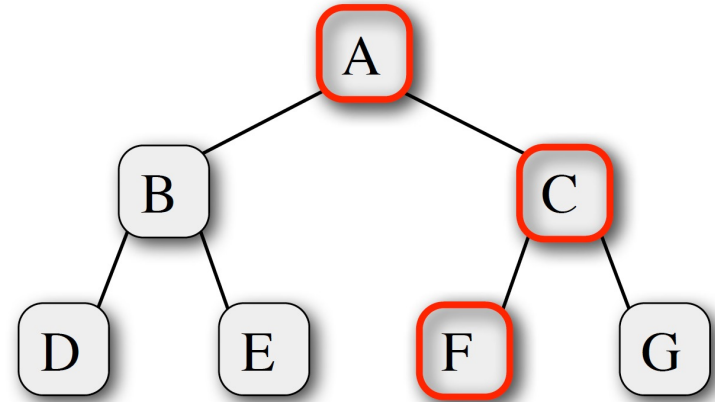
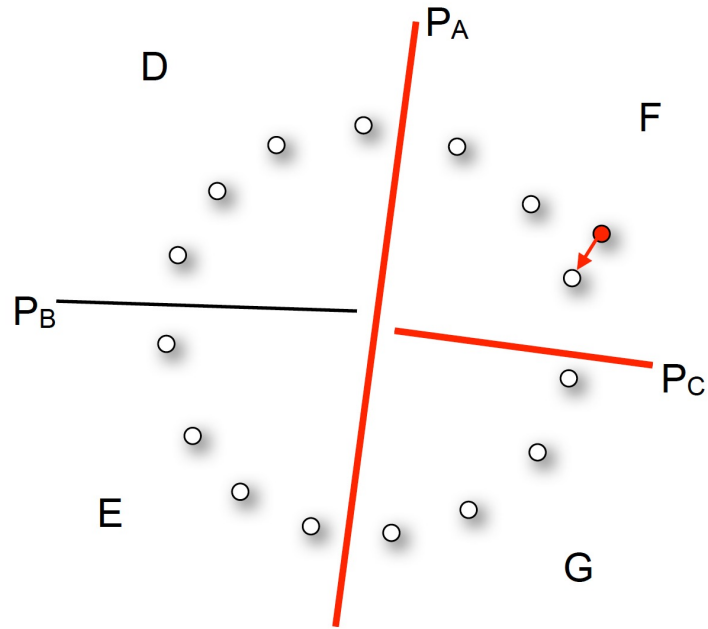


BSP Closest Point

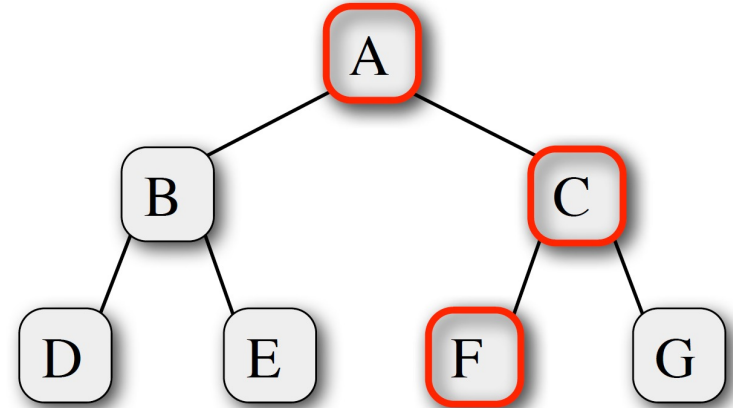
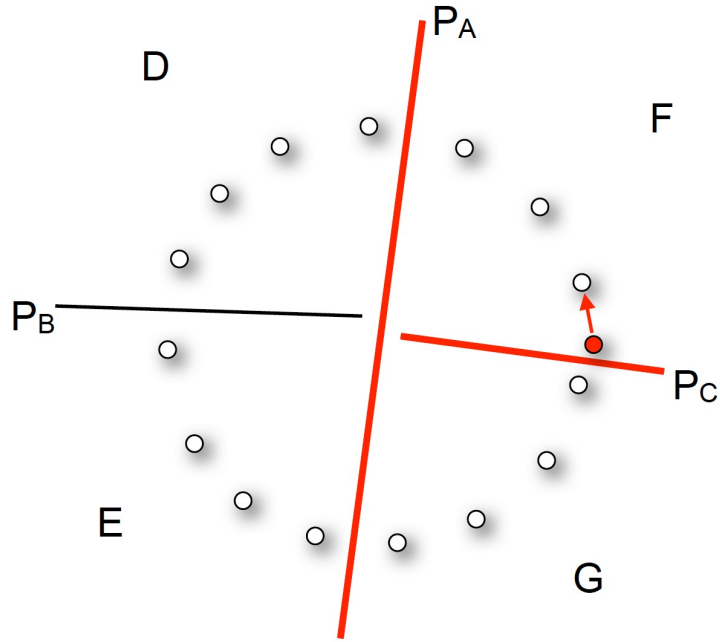
```
BSPNode::dist(Point x, Scalar& dmin)
{
    if (leaf_node())
        for each sample point p[i]
            dmin = min(dmin, dist(x, p[i]));

    else
    {
        d = dist_to_plane(x);
        if (d < 0)
        {
            left_child->dist(x, dmin);
            if (|d| < dmin) right_child->dist(x, dmin);
        }
        else
        {
            right_child->dist(x, dmin);
            if (|d| < dmin) left_child->dist(x, dmin);
        }
    }
}
```

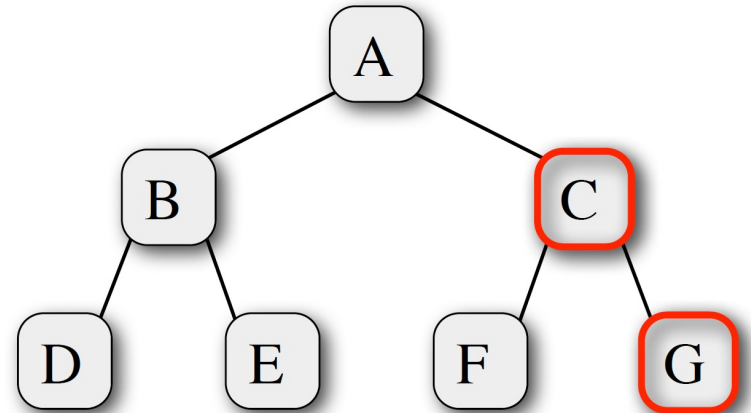
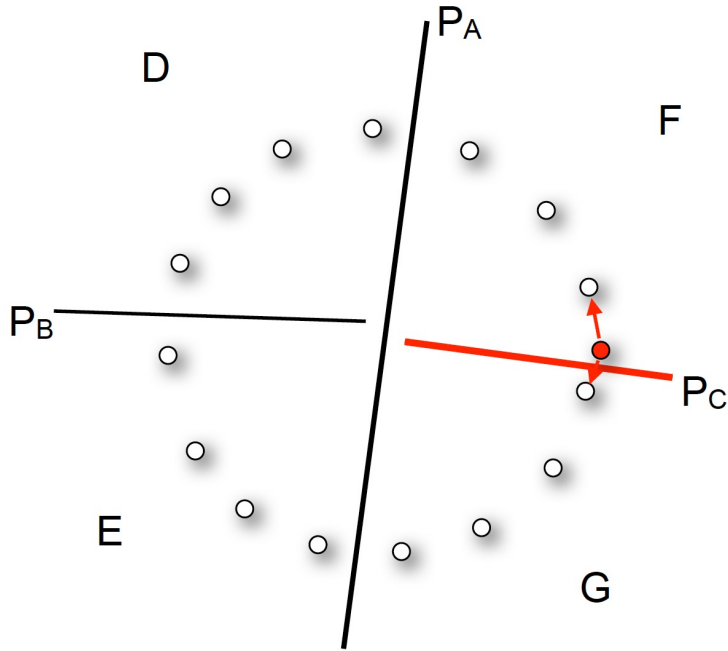
BSP Closest Point



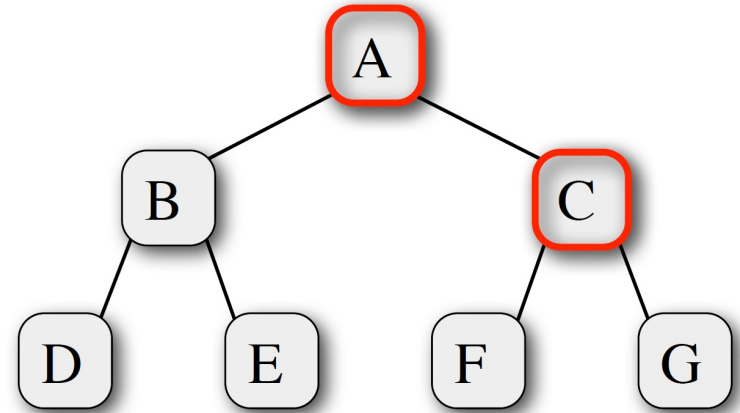
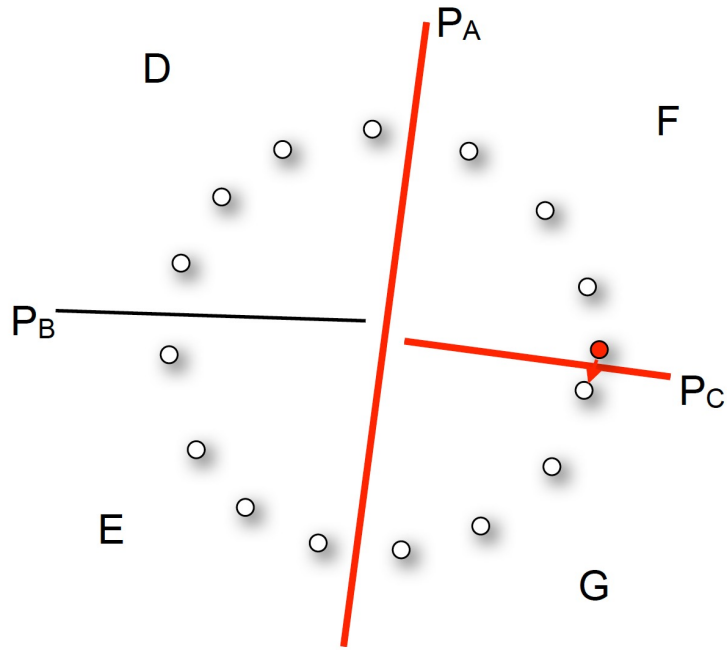
BSP Closest Point



BSP Closest Point



BSP Closest Point



ICP Variants

- Variants on the following stages of ICP have been proposed:
 - Selecting sample points (from one or both meshes)
 - Matching to points in the other mesh
 - Weighting the correspondences
 - Rejecting certain (outlier) point pairs
 - Assigning an error metric to the current transform
 - Minimizing the error metric w.r.t. transformation

Real Time ICP

