3D Data Processing

Point Clouds Descriptor

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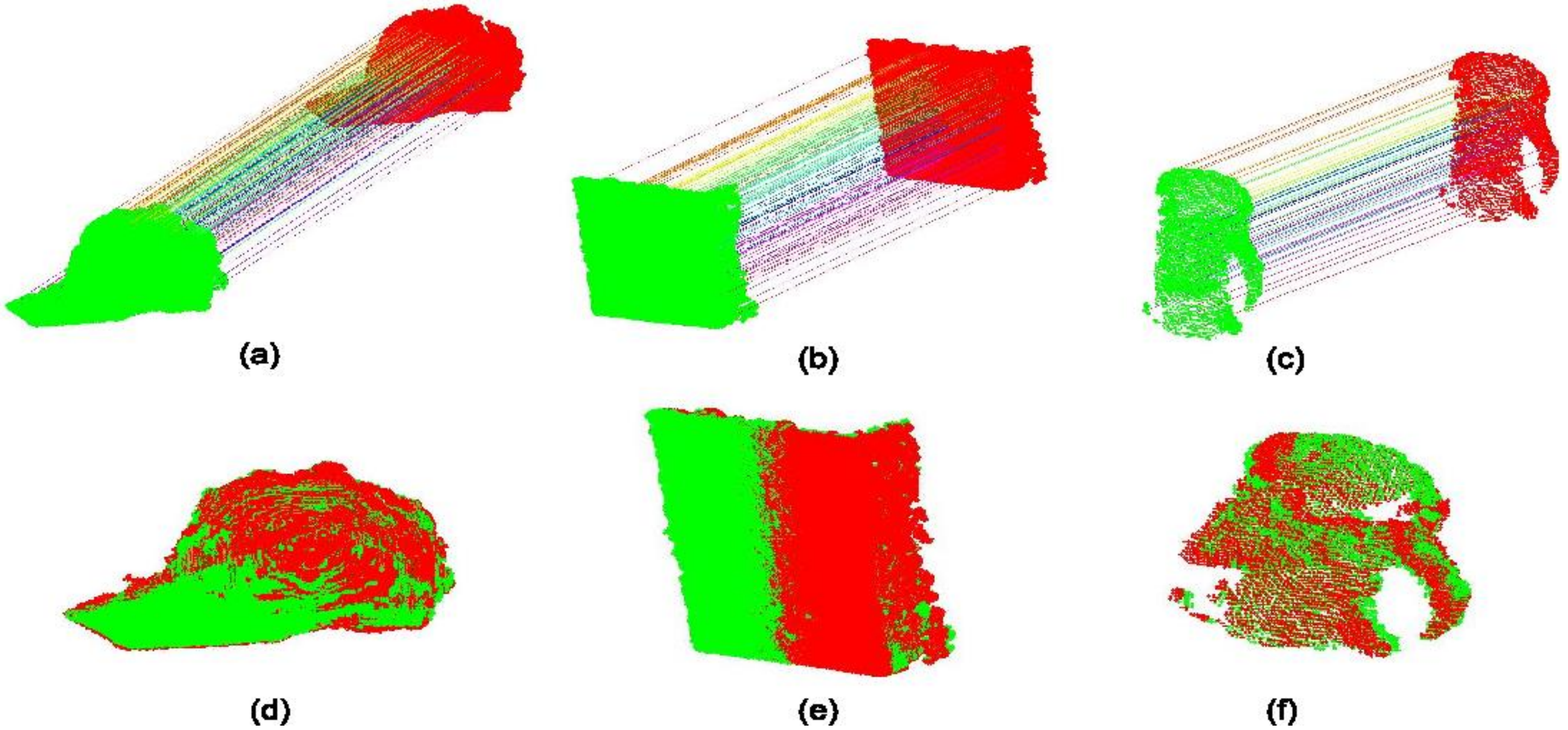
Today

- PFH (Point Feature Histogram)
- FPFH (Fast Point Feature Histogram)
- RSD (Radius-Based Surface Descriptor)
- 3DSC (3D Shape Context)
- SHOT (Signatures of Histograms of Orientations)
- NARF (Normal Aligned Radial Feature)

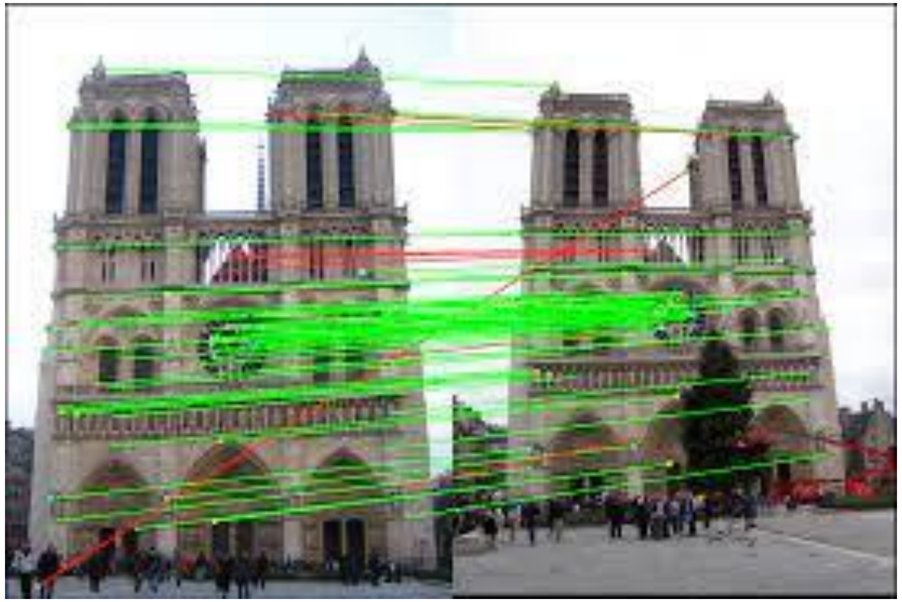
3D feature matching

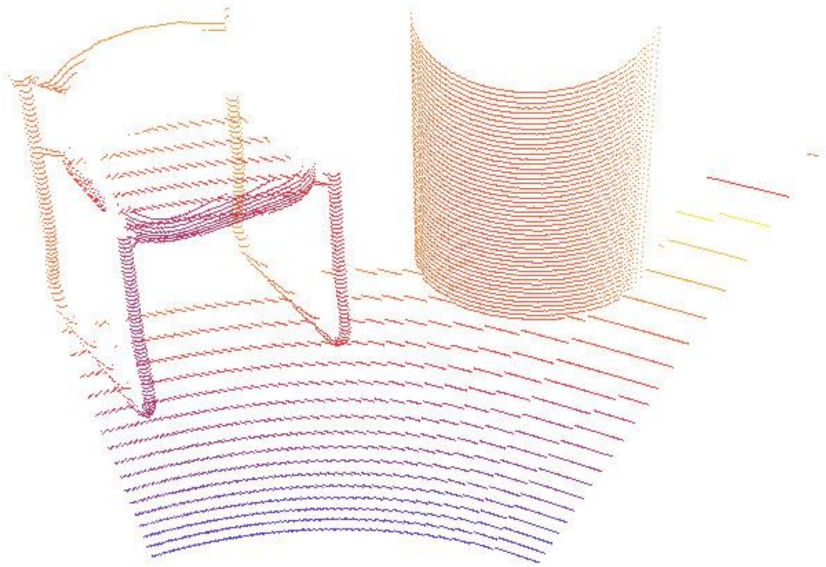
- Feature matching
  - Classification
  - Registration
  - Pose estimation



3D feature matching

- Differences to 2D features
  - Many methods are focused on descriptors.
  - It’s hard to define feature point (lack of texture)
  - Write a descriptor for every point after downsampling





3D descriptors

- 3D features(descriptor) should follows:
  - Robust to transformations
    - Rigid transformations must not affect the feature
  - Robust to noise
    - measurement errors that cause noise should not change the feature estimation much
  - Resolution invariant
    - if sampled with different density (like after performing downsampling), the result must be identical or similar

3D Descriptors

- Local descriptors are computed for individual points
- No notion of what an object is, they just describe how the local geometry is around that point.
- Feature Point
  - downsampling and choosing all remaining points

PFH (Point Feature Histogram)

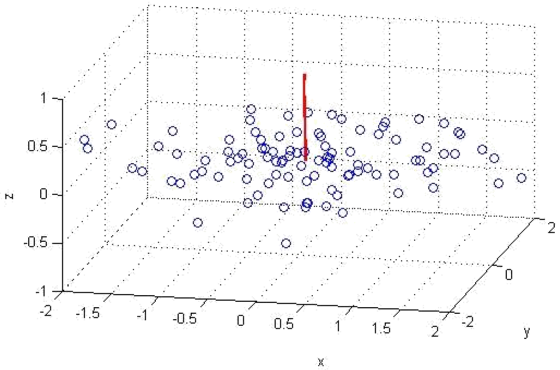
- Capture information of the geometry surrounding the point
- Analyzing the difference between the directions of the normals in the vicinity
    - algorithm pairs all points in the vicinity
    - a fixed coordinate frame is computed from their normal
    - the difference between the normals can be encoded with <u>3 angular variables</u>
    - 3 angular variables + euclidean distance between the points
    - All pairs of vicinity are computed → binning to histogram

vicinity: points in a shpere

Semantic 3D Object Maps for Everyday Manipulation in Human Living Environments, 2009

PFH (Point Feature Histogram)

- Normal vector estimation
  - Using the simplest method is based on the first order 3D plane fitting
  - P_k: A point cloud consisting of p and its k-neighbors.
  - Normal vector n is perpendicular to a plane consisting P_k



$$x = \overline{p} = \frac{1}{k} \cdot \sum_{i=1}^{k} p_i$$

$$\mathcal{C} = \frac{1}{k} \sum_{i=1}^{k} \xi_i \cdot (p_i - \overline{p}) \cdot (p_i - \overline{p})^T, \; \mathcal{C} \cdot \vec{v}_j = \lambda_j \cdot \vec{v}_j, \; j \in \{0, 1, 2\}$$

  - The eigen vector, of which eigen value is the smallest is normal vector n
  - Represented in spherical coordinate:

$$\phi = \arctan\left(\frac{n_z}{n_y}\right), \; \theta = \arctan \frac{\sqrt{(n_y^2 + n_z^2)}}{n_x}$$

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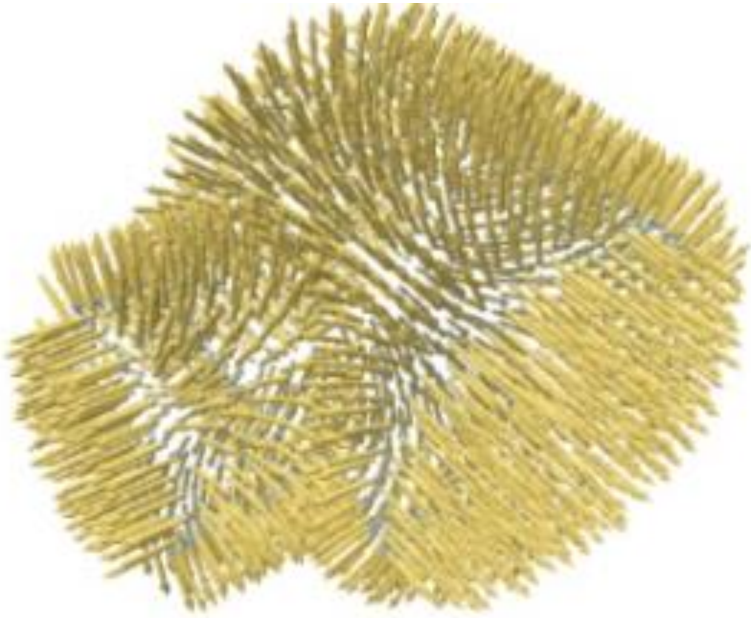
PFH (Point Feature Histogram)

- Normal vector estimation

Point clouds



normal vector

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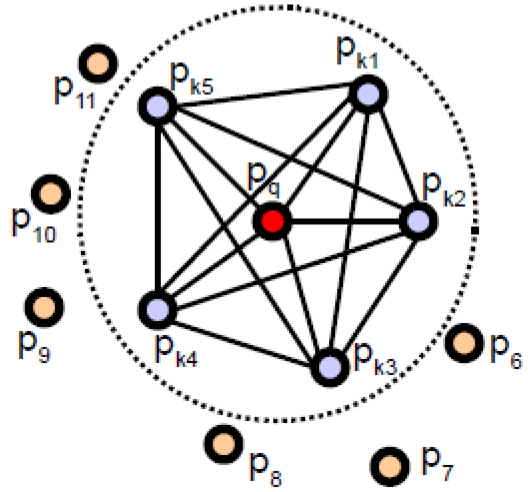
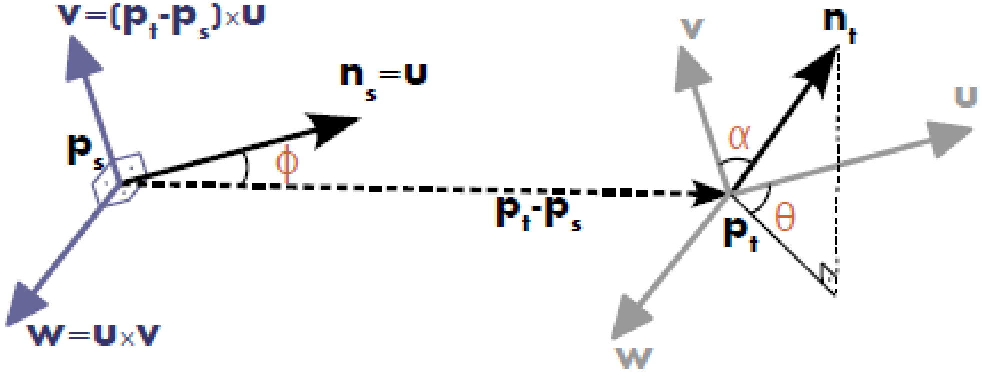
PFH (Point Feature Histogram)

- The quadruplet $< \alpha, \phi, \theta, d >$ of two points
  - There are $k\frac{k-1}{2}$ quadruplet per a group (vicinity)



The query point
(red) and its k-neighbors (blue) are
fully interconnected in a mesh.



$$\begin{cases} \mathrm{u} = n_s \\ \mathrm{v} = \mathrm{u} \times \dfrac{(p_t - p_s)}{\|p_t - p_s\|_2} \\ \mathrm{w} = \mathrm{u} \times \mathrm{v} \end{cases}$$

$$\alpha = \mathrm{v} \cdot n_t$$

$$\phi = \mathrm{u} \cdot \frac{(p_t - p_s)}{d}$$

$$\theta = \arctan(\mathrm{w} \cdot n_t, \mathrm{u} \cdot n_t)$$

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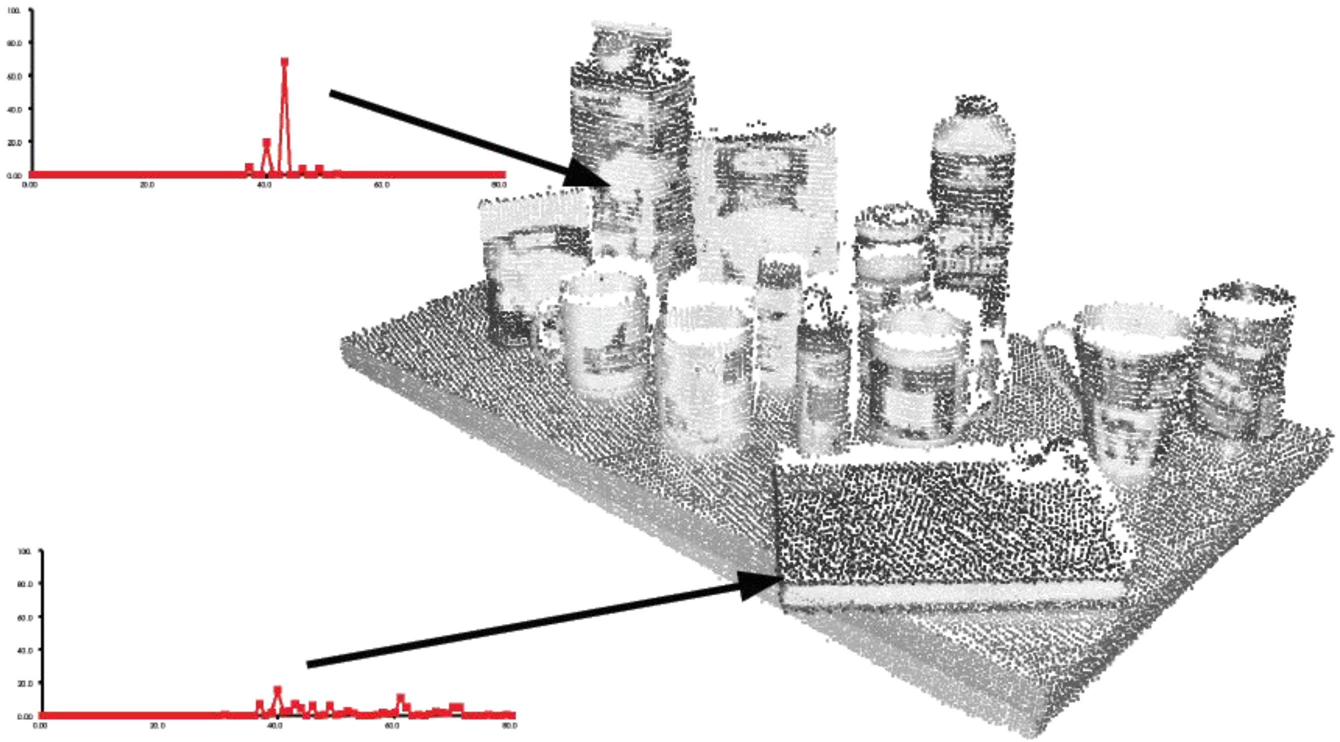
PFH (Point Feature Histogram)

- PFH representation for the query point p
  - all quadruplets is binned into a histogram.
  - each features's value range into b subdivisions
  - counts the number of occurrences in each subinterval



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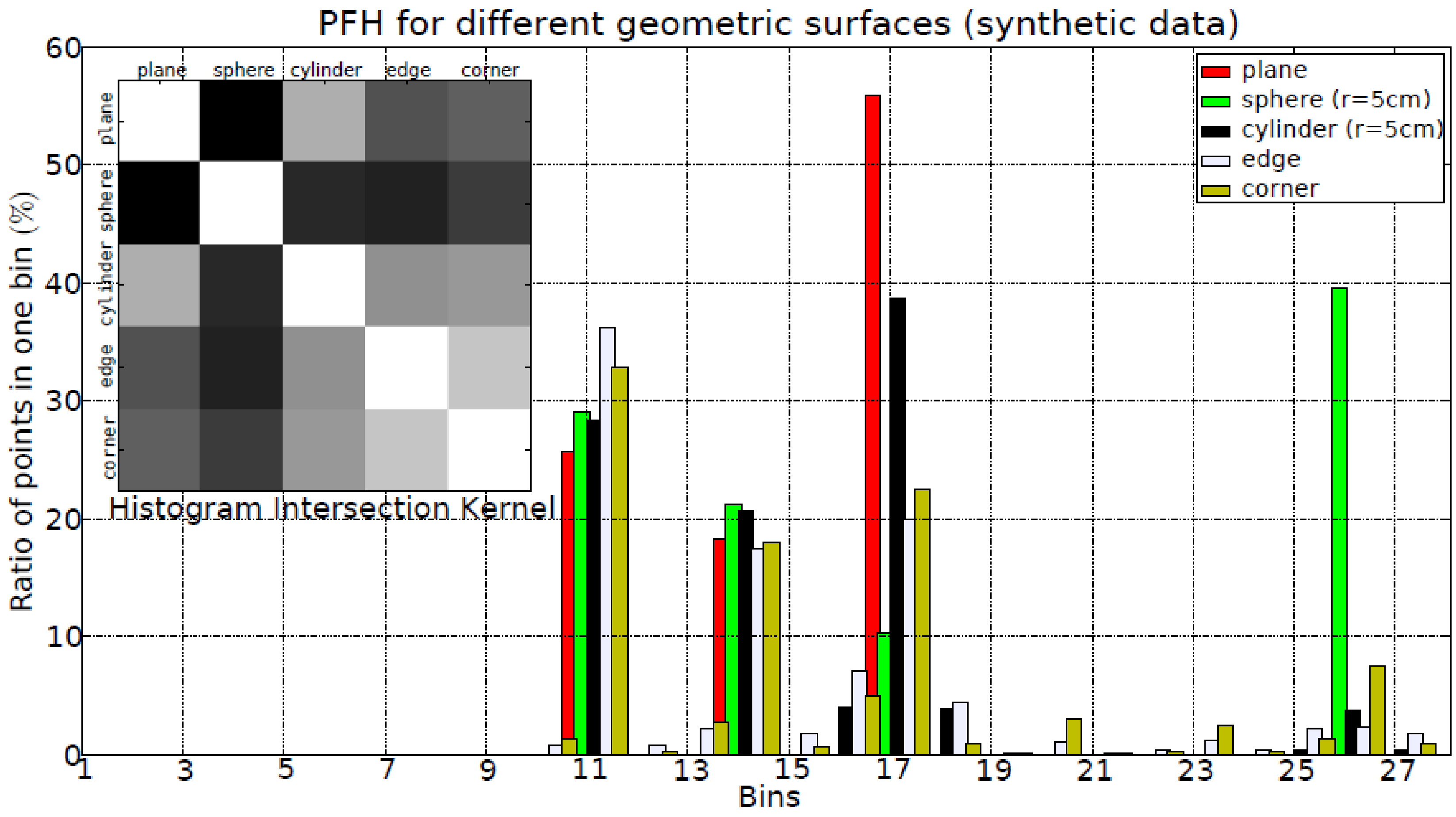
PFH (Point Feature Histogram)

- Example of Point Feature Histograms



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FPFH (Fast Point Feature Histogram)

- PFH gives accurate results, but it has a drawback
  - It is too computationally expensive to perform at real time
  - complexity of $O(nk^2)$.

- FPFH reduce the complexity of PFH
  - complexity of $O(nk)$.

- the FPFH does not fully interconnect all neighbors of p_q
- the FPFH includes additional point pairs outside the r radius sphere

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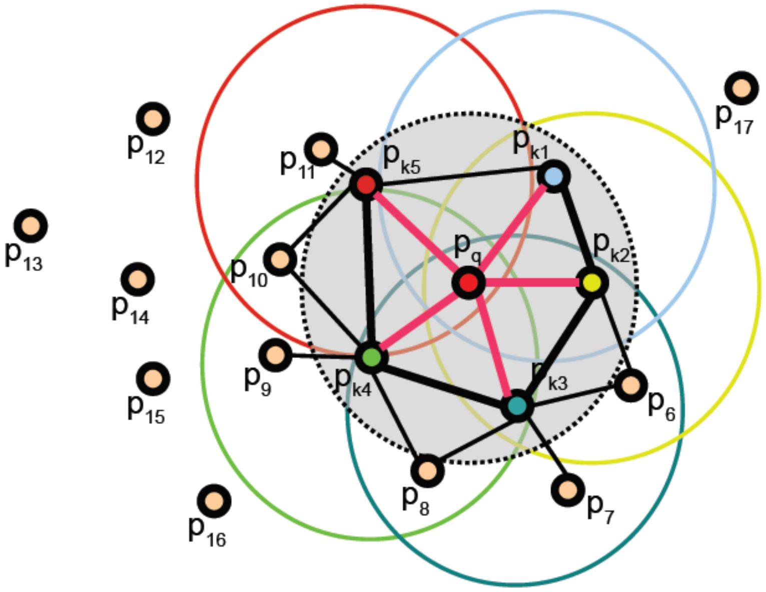
FPFH (Fast Point Feature Histogram)

- Simplified Point Feature Histogram (SPFH)
  - for each query point p_q a set of tuples $< \alpha, \phi, \theta >$ between itself and its neighbors
    - No features are calculated among other points in vicinity
  - FPFH: SPFH values are used to weight the final histogram of p_q

$$FPFH(\boldsymbol{p}_q) = SPFH(\boldsymbol{p}_q) + \frac{1}{k}\sum_{i=1}^{k}\frac{1}{\omega_k}\cdot SPFH(\boldsymbol{p}_k)$$



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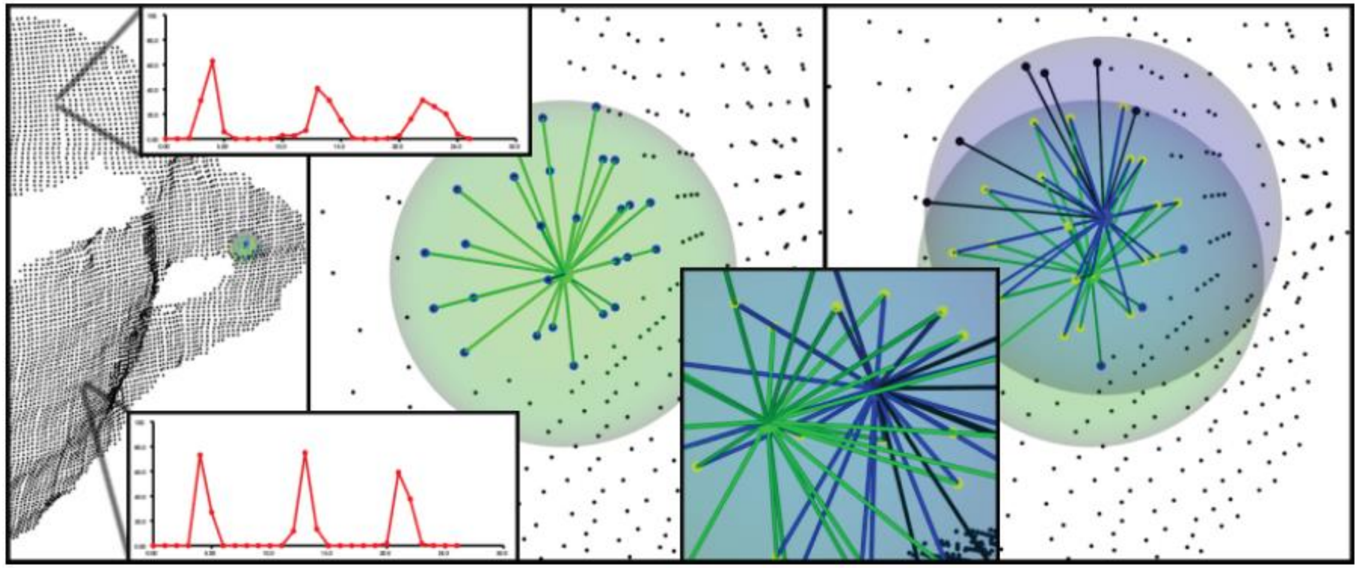

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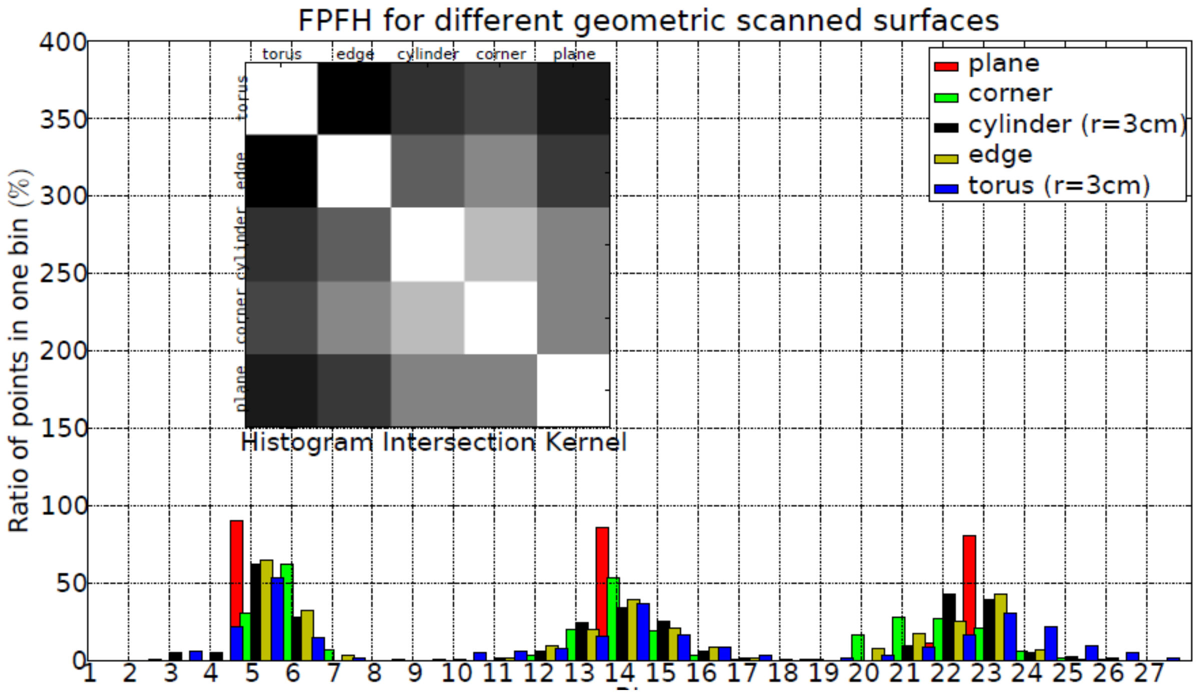
FPFH (Fast Point Feature Histogram)

- Decorrelated Histogram
- FPH using correlated histogram
  - Ex) feature number is d, subdivision number is d, then histogram dimension is b^d
- FPFH concatenate each subdivisions (such as SIFT)



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FPFH (Fast Point Feature Histogram)

- Other ideas to speed-up
- Caching and Point Ordering technique
  - If p and q are the each other's neighborhood, recomputing is wasting time!
  - Caching with FIFO basis! -> Reusing
- Caching with point ordering is efficient
  - Temporal locality in the cache! => Close points should have indices which are close together.
  - Right experiments : randomly indexed time VS reordered time(Red to Blue means large index)

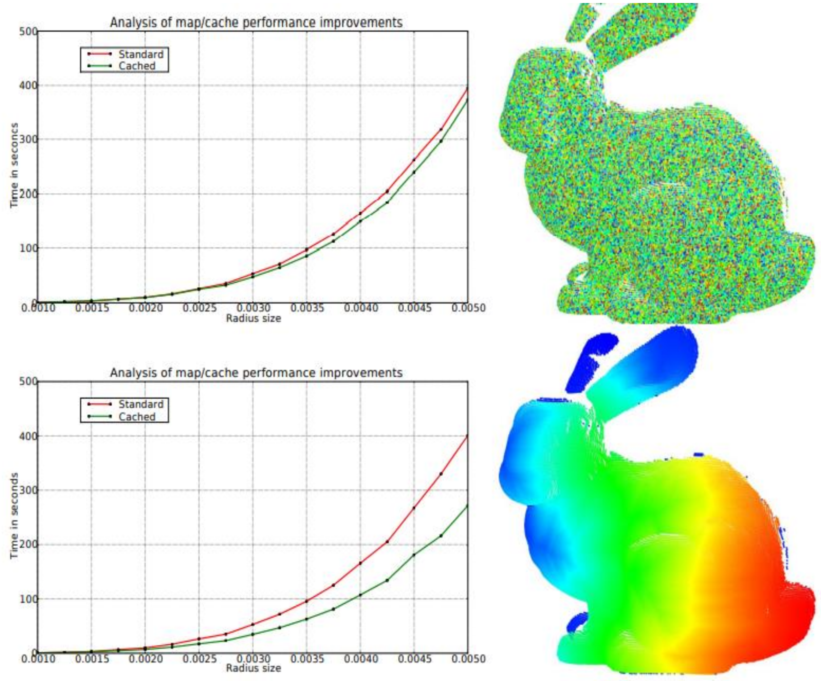

Fig. 4. Complexity Analysis on Point Feature Histograms computations for the bunny00 dataset: unordered (top), and reordered (bottom).

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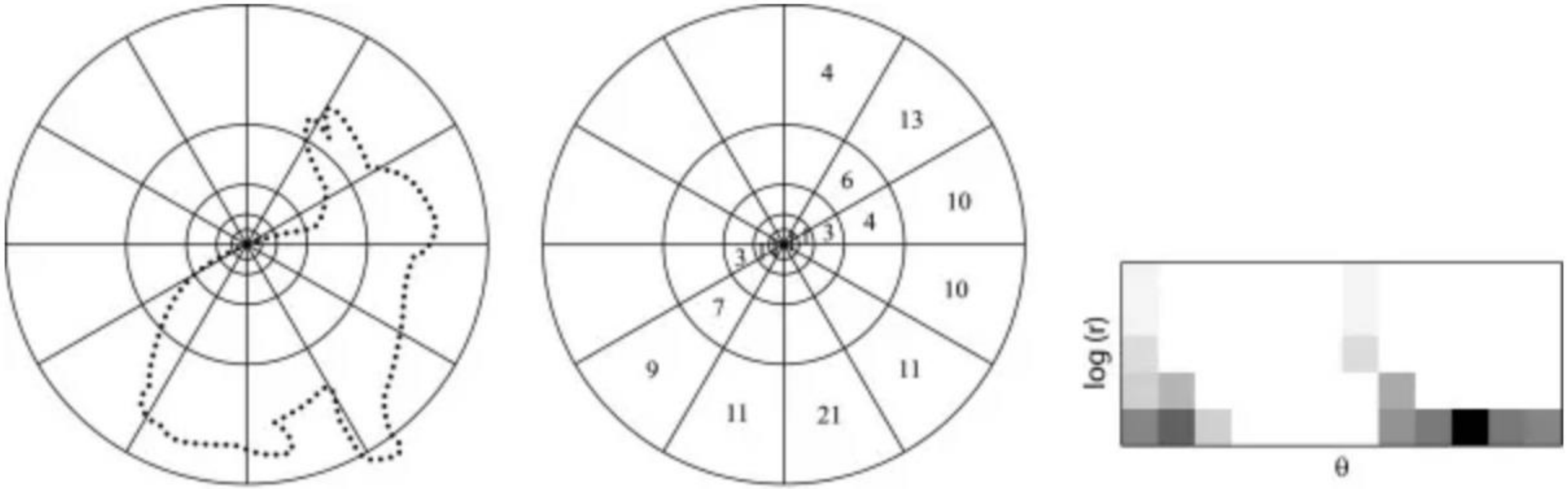
3DSC

- 2D Shape context
  - Local descriptor of points and their neighborhood
  - Count the number of points inside each bin
  - Compact representation of distribution of points relative to each point

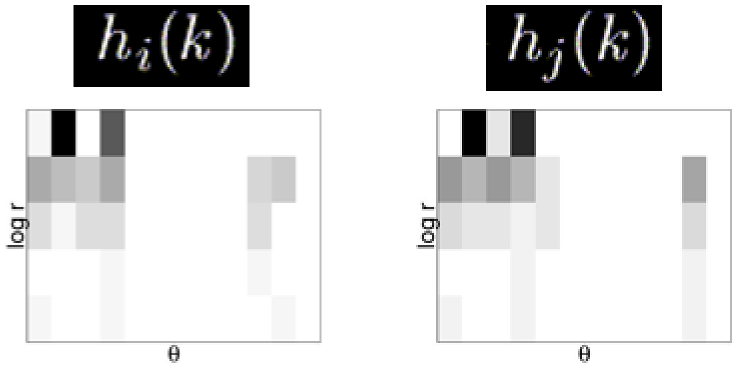


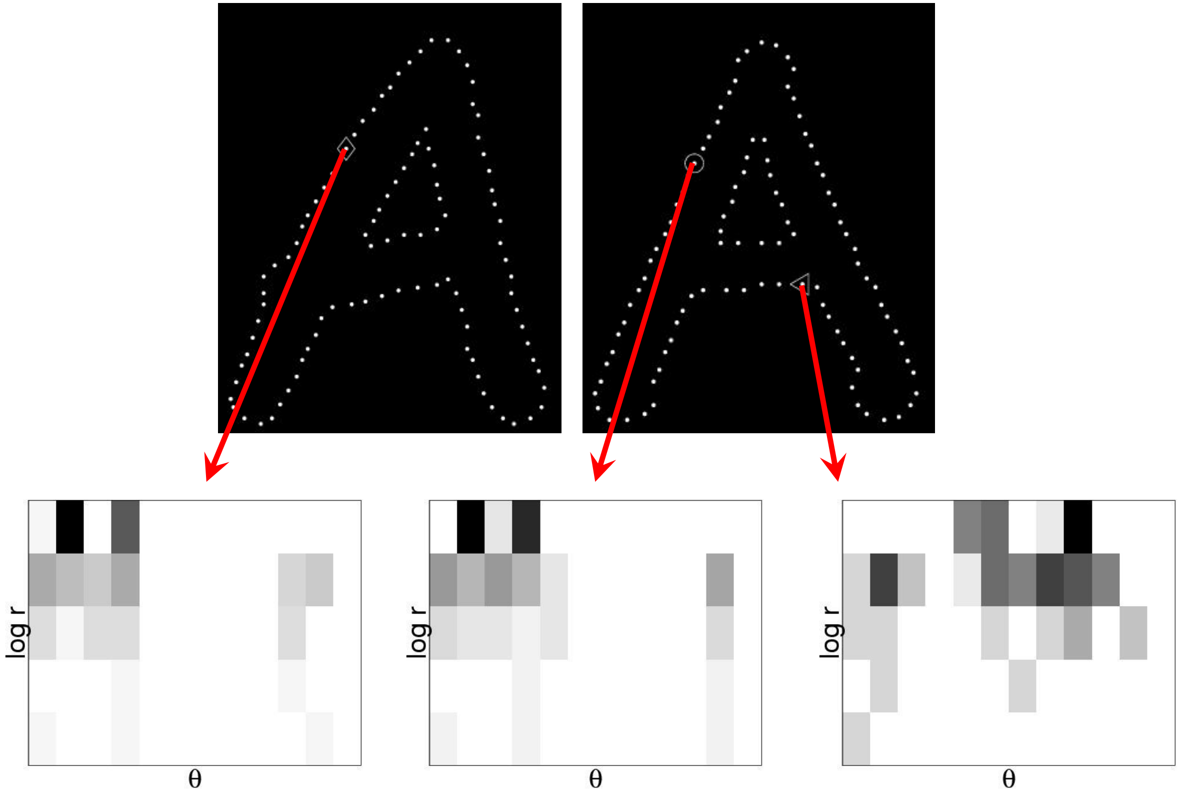
Shape Context: A new descriptor for shape matching and object recognition , NIPS, 2000

3DSC

- Comparing 2D Shape context
  - An example

$$C_{ij} = \frac{1}{2}\sum_{k=1}^{K}\frac{\left[h_i(k) - h_j(k)\right]^2}{h_i(k) + h_j(k)}$$

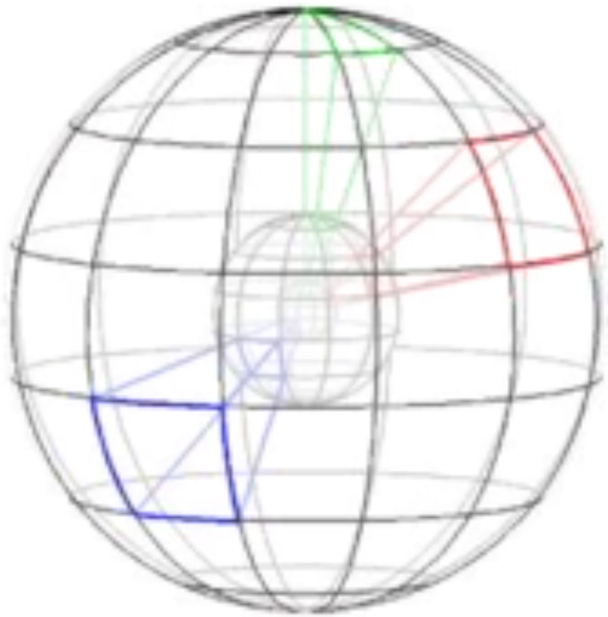




Shape Context: A new descriptor for shape matching and object recognition , NIPS, 2000

3DSC

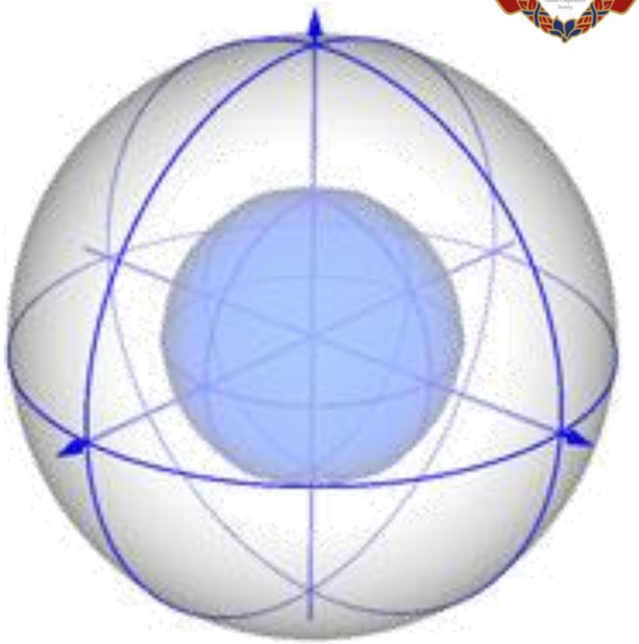
- 3D Shape Context
  - 3D Shape Context is a descriptor that extends its existing 2D counterpart to the third dimension
  - The "north pole" of that sphere → normal vector
  - Not invariant to in-plane rotation
  - the sphere is divided in 3D regions or bins
    - 2 coordinates (azimuth and elevation): equally spaced
    - radial dimension: logarithmically spaced



Recognizing objects in range data using regional point descriptors, ECCV, 2004

SHOT

- Signature of Histogram of OrienTation
  - encodes information about the topology (surface) withing a spherical support structure.
  - For every volume, a one-dimensional local histogram is computed. → rotation invariance
  - Sphere is divided in 32 bins or volumes
    - 8 divisions along the azimuth
    - 2 along the elevation
    - 2 along the radius



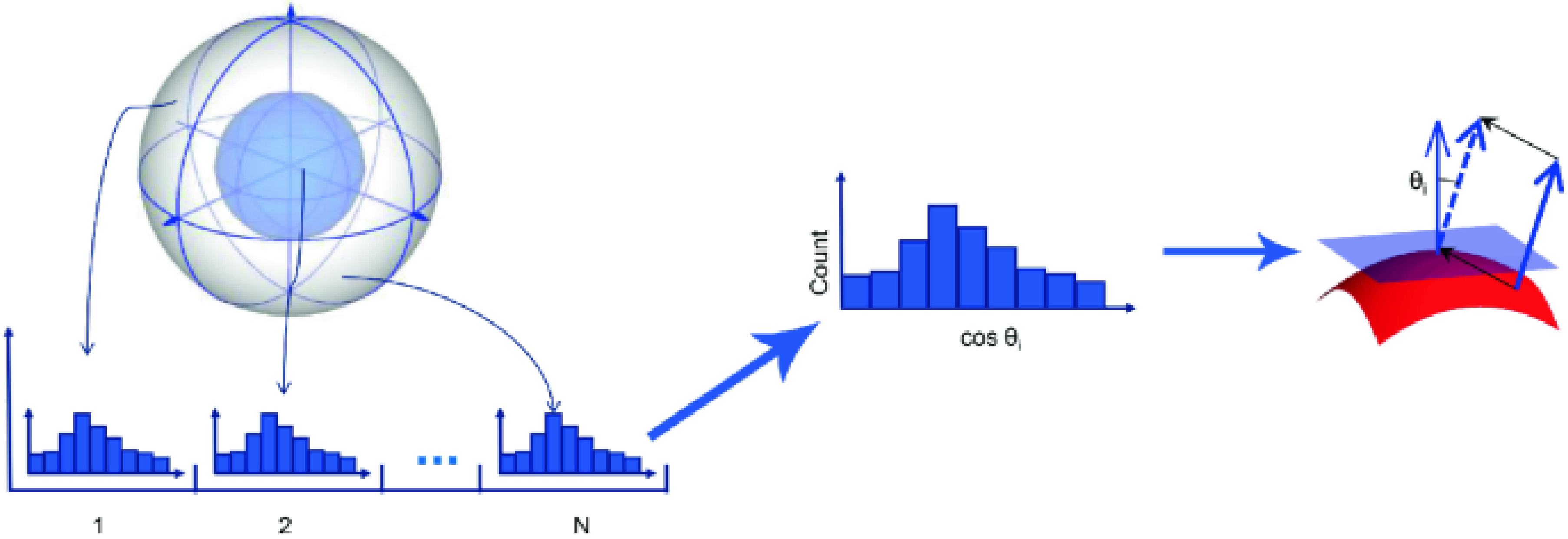
Recognizing objects in range data using regional point descriptors, ECCV, 2004

SHOT

- Descriptor
  - Angles of normal vector of the query and the target points

$$\cos_{\theta_i} = n_s \cdot n_i$$

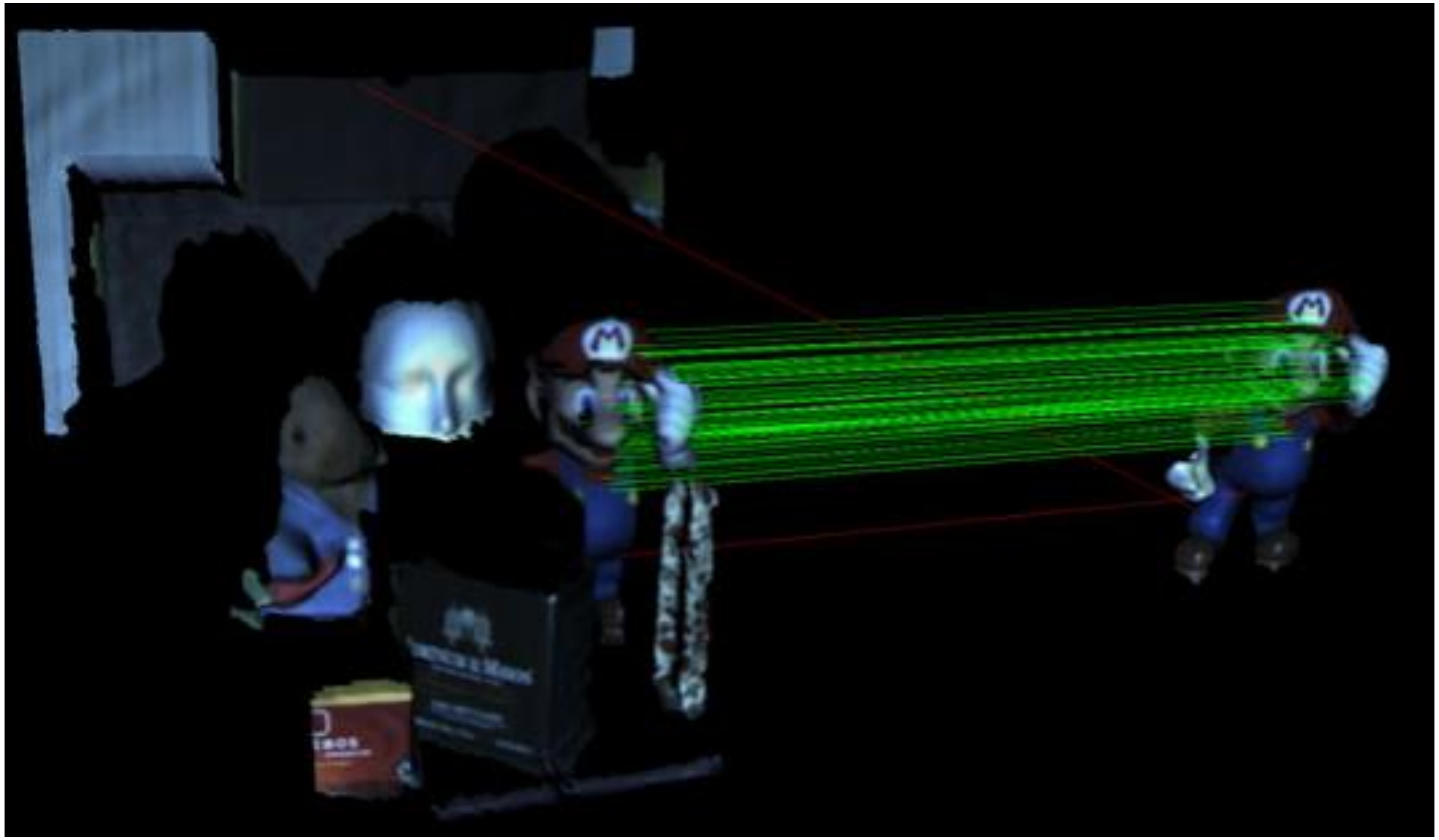
  - Quantized to 11bins: 32bins(grid) x 11bins(angle) = 352 dim



Unique Signatures of Histograms for Local Surface Description , ECCV, 2010

SHOT

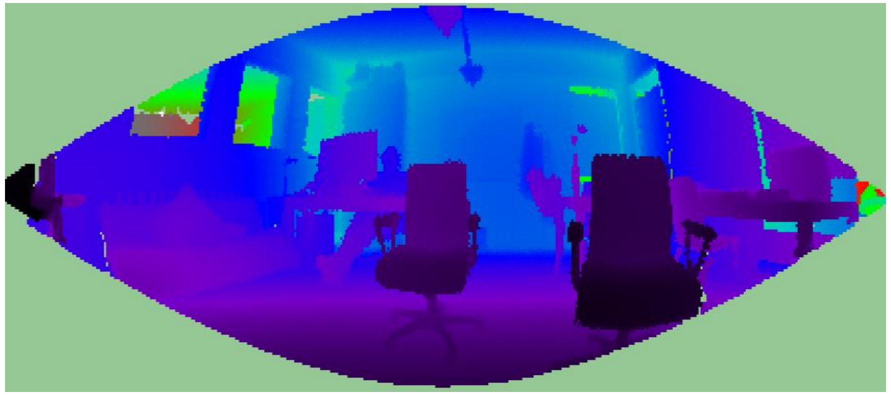
- A matching example



Unique Signatures of Histograms for Local Surface Description , ECCV, 2010

NARF

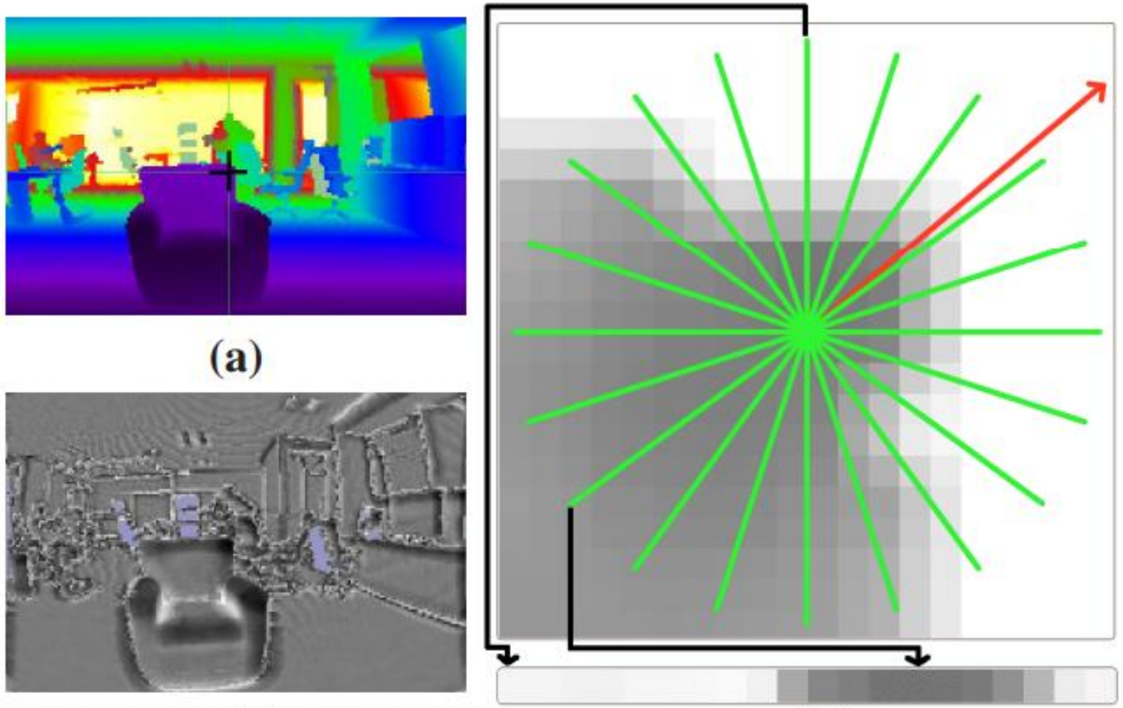
- Normal Aligned Radial Feature
- 3D Range Image Features for Object Recognition
- Depth image-based method
  - 2D-image with pixel values representing depth
  - Allows border extraction
- Uses borders and change in distance (pixel) values to identify key points
- Key points are invariant to scale, susceptible to camera orientation



NARF: 3D Range Image Features for Object Recognition, ECCV, 2010

NARF

- NARF descriptor
  - calculate a normal aligned range value patch in the point
  - overlay a star pattern onto this patch
  - extract a unique orientation from the descriptor
  - shift the descriptor according to this value to make it invariant to the rotation



(a) (c) (b)

NARF: 3D Range Image Features for Object Recognition, ECCV, 2010

Thank you