Keypoints and Features

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A feature..what?

Etymology

From Anglo-Norman *feture*, from Old French *faiture*, from Latin *factura*.

Pronunciation

- (*UK*) IPA: /fiːtʃə(ɹ)/, X-SAMPA: /fi:tS@(r)/
- Audio (US) 0:00 MENU
- Rhymes: -iːtʃə(ɹ)

Noun

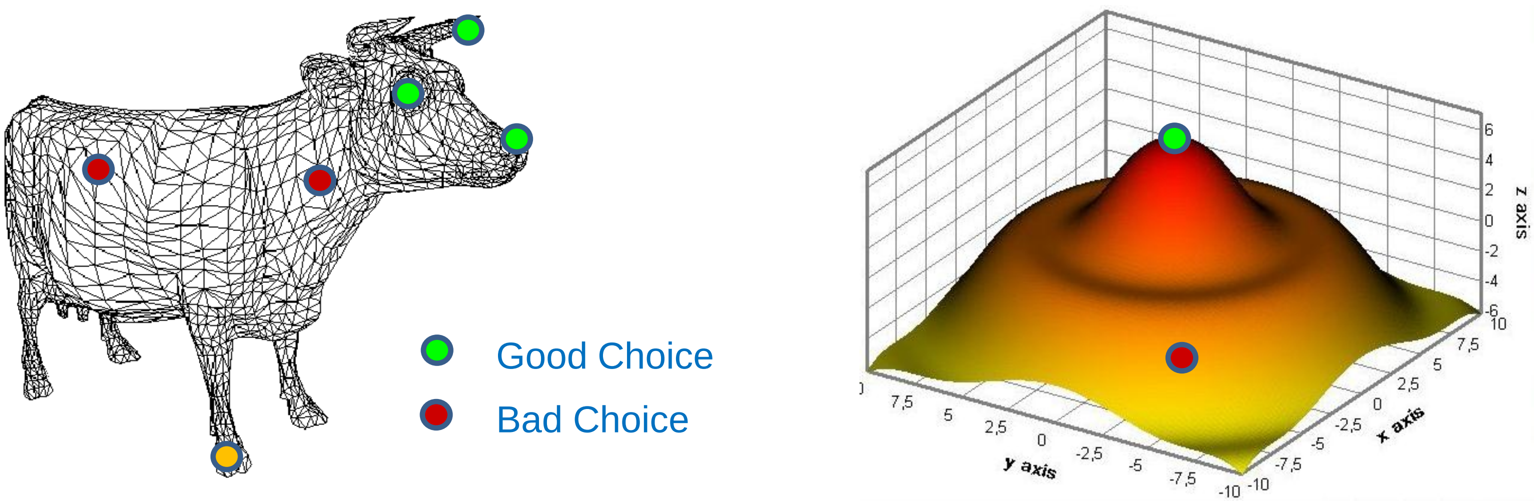
feature (*plural* **features**)

1. (*obsolete*) One's structure or make-up; form, shape, bodily proportions. [quotations ▼]
2. An important or main item.
3. (*media*) A long, prominent, article or item in the media, or the department that creates them; frequently used technically to distinguish content from news.
4. Any of the physical constituents of the face (eyes, nose, etc.).
5. (*computing*) A beneficial capability of a piece of software. [quotations ▼]
6. The cast or structure of anything, or of any part of a thing, as of a landscape, a picture, a treaty, or an essay; any marked peculiarity or characteristic; as, one of the features of the landscape. [quotations ▼]
7. (*archaeology*) Something discerned from physical evidence that helps define, identify, characterize, and interpret an archeological site. [quotations ▼]
8. (*engineering*) Characteristic forms or shapes of a part. For example, a hole, boss, slot, cut, chamfer, or fillet.

- Feature is a compact – but *rich* – *representation* of our (3D) data
- It is designed to be invariant (or robust) to a specific class of transformations and/or set of disturbances

3D keypoint detection

- **3D keypoints** are
  - **Distinctive**, i.e. suitable for effective description and matching (*globally definable*)
  - **Repeatable** with respect to point-of-view variations, noise, etc… (*locally defin*able)
- Usually scale-invariance is not an issue (but better if each feature is extracted together with its characteristic scale)



Distinctiveness vs. repeatability

pcl::Keypoints

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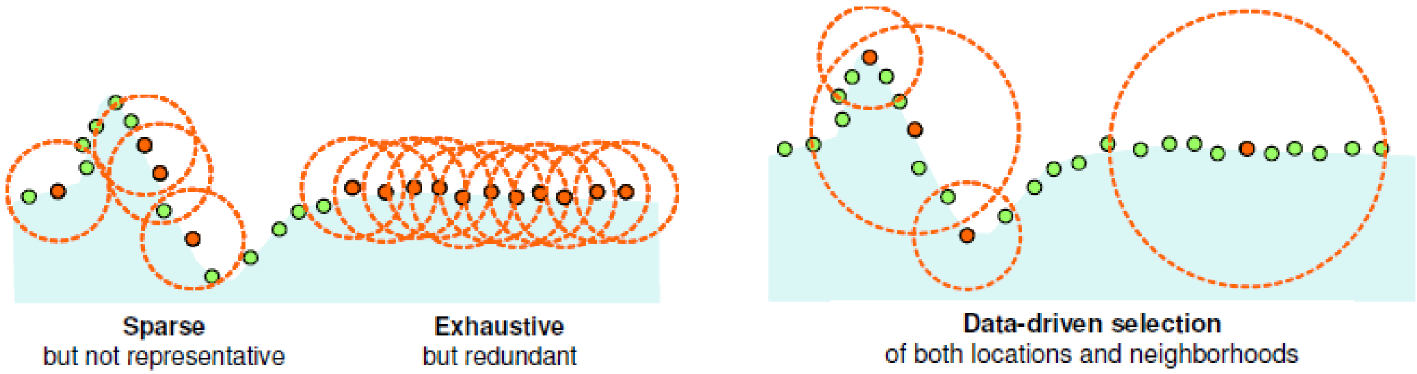
- (for now) a small set of detectors specifically proposed for 3D point clouds and range maps
  - Intrinsic Shape Signatures (ISS) [Zhong ICCVW09]
  - NARF [Steder ICRA11]
  - Uniform Sampling *(*basically a *voxelGrid*, where selected points are a subset of the input cloud)

- Several detectors «derived» from 2D interest point detectors
  - Harris (2D, 3D, 6D) [Harris AVC88] - CD
  - SIFT [Lowe IJCV04] - BD
  - SUSAN [Smith IJCV95] - CD
  - AGAST [Mair ECCV10] - CD

Taxonomy



Courtesy of Unnikrishnan & Hebert

- In the context of most PCL applications scale is not an issue

BUT

- The characteristic scale is still an important property of a 3D keypoint
- Several recent proposals, two main categories [Tombari IJCV13]
  - **Fixed-scale detectors:** all keypoints are detected at a specific scale (input parameter)
  - **Adaptive-scale detectors:** specific scale-space analysis to detect salient structures at multiple scales, associating each keypoint a **characteristic scale**
- Need for performance assessment
  - Locality repeatability / Quantity, Scale repeatability, Efficiency
  - ***www.vision.deis.unibo.it/keypoints3d***

Intrinsic Shape Signatures

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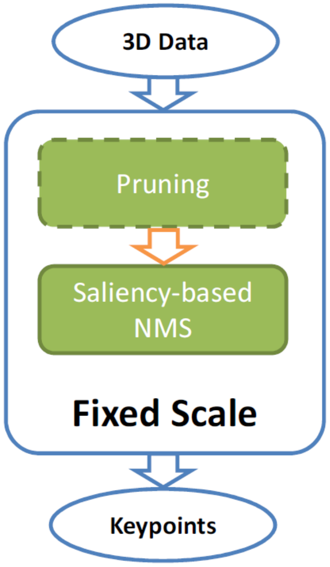
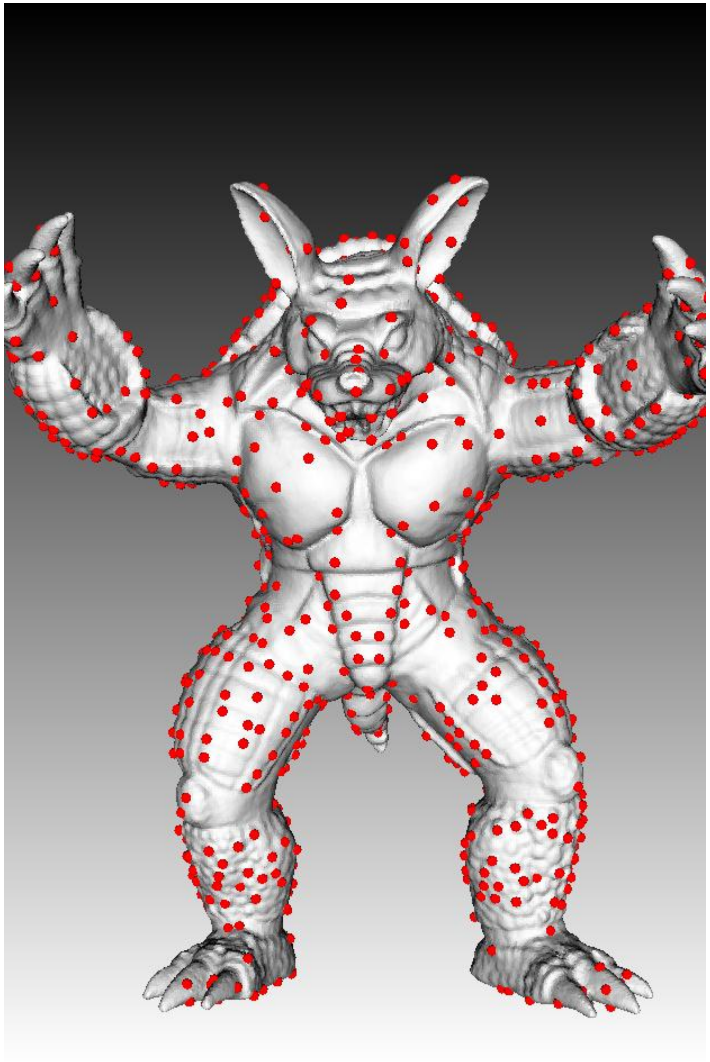
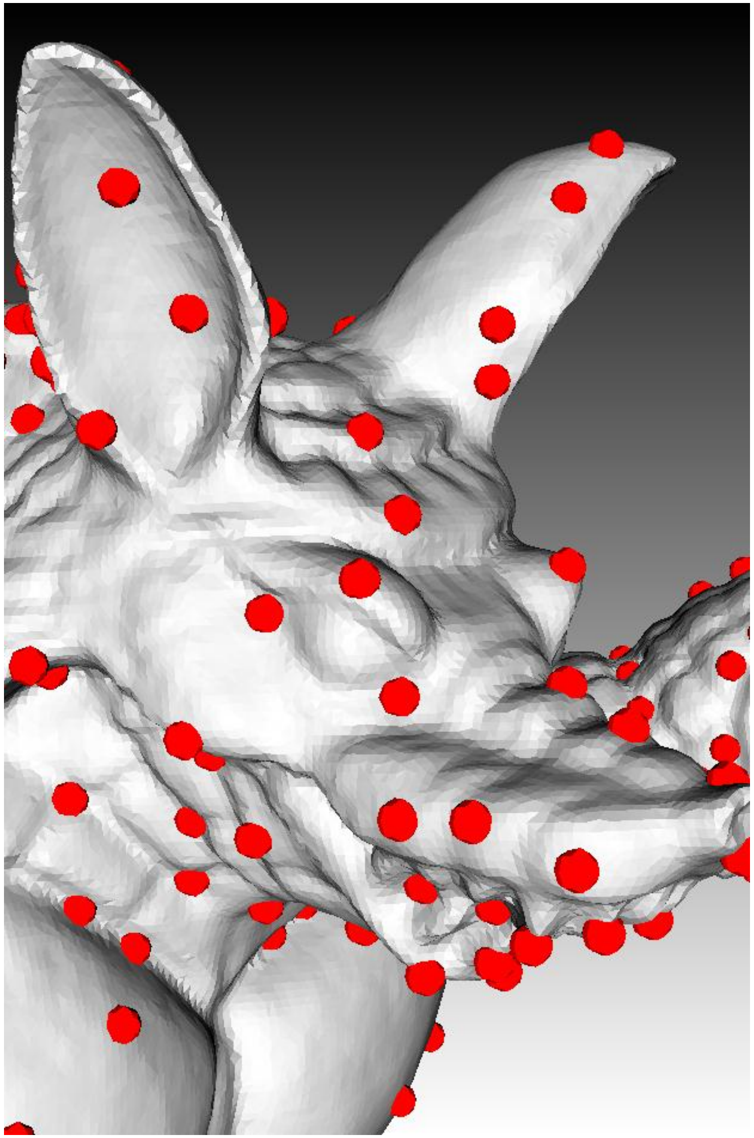
- Exploits the covariance matrix $$\mathbf{M}(\mathbf{p}_i) = \frac{1}{\sum_{j=1}^{k} \rho_i} \sum_{j=1}^{k} \rho_i (\mathbf{p}_j - \mathbf{p}_i)(\mathbf{p}_j - \mathbf{p}_i)^T$$
- Let its eigenvalues, in decreasing magnitude order, be
$$\lambda_1, \lambda_2, \lambda_3$$
- The pruning step discards points with similar spreads along the principal directions, where a repeatable LRF cannot be defined
$$\frac{\lambda_2(\mathbf{p})}{\lambda_1(\mathbf{p})} < Th_{12} \ \wedge \ \frac{\lambda_3(\mathbf{p})}{\lambda_2(\mathbf{p})} < Th_{23}$$



- Saliency is the magnitude of the third eigenvalue $\rho(\mathbf{p}) \doteq \lambda_3(\mathbf{p})$
- Non-Maxima Suppression (NMS) over saliency
- It includes only points with large variations along each principal direction
- “Winner” of PCL 3D detector evaluation in [Filipe 2013]

Intrinsic Shape Signatures





Example

UNIFORM SAMPLING

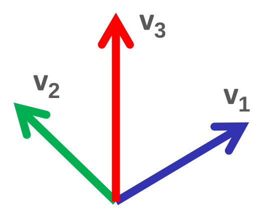
```
pcl::PointCloud<int> indices;
pcl::UniformSampling<pcl::PointXYZ> uniform_sampling;
uniform_sampling.setInputCloud (cloud);
uniform_sampling.setRadiusSearch (0.05f); //the 3D grid leaf size
uniform_sampling.compute (indices);
```

ISS

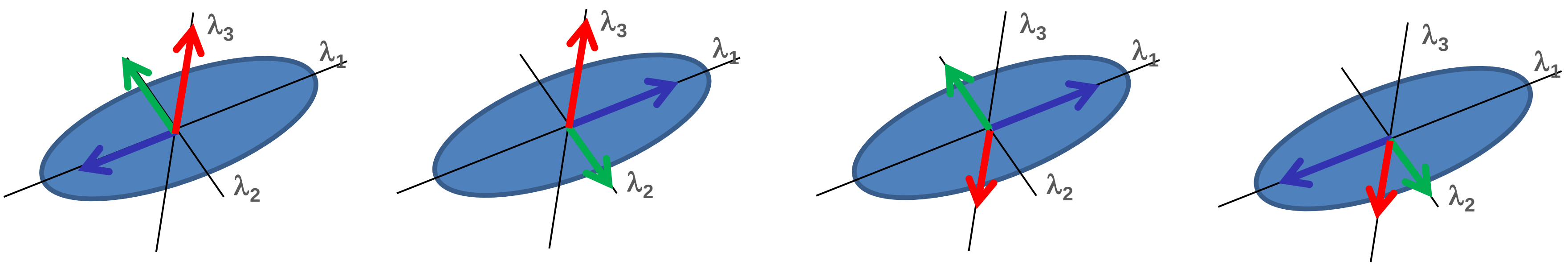
```
pcl::PointCloud<pcl::PointXYZ>::Ptr keypoints (new
pcl::PointCloud<pcl::PointXYZ>());
pcl::ISSKeypoint3D<pcl::PointXYZ, pcl::PointXYZ> iss_detector;
iss_detector.setSalientRadius (support_radius);
iss_detector.setNonMaxRadius (nms_radius);
iss_detector.setInputCloud (cloud);
iss_detector.compute (*keypoints);
```

Local Reference Frame

- 3 orthogonal unit vectors defined upon a local support
- Goal:
  - invariant to rotations and translations
  - robust to noise and clutter



- Common approach to deal with ambiguities in the LRF definition
  - Define **multiple LRFs** at each keypoint, providing multiple descriptions of the same keypoint
  - Cons:
    - more descriptors to be computed and matched (less efficient)
    - ambiguity pushed to the matching stage
  - Eg. EVD of the scatter matrix computed over the support as used in [Mian10] [Novatnack08] [Zhong09], provides 3 repeatable directions but **no repeatable sign** [Tombari10]
  - 4 different RFs can be obtained by enforcing the right-hand rule

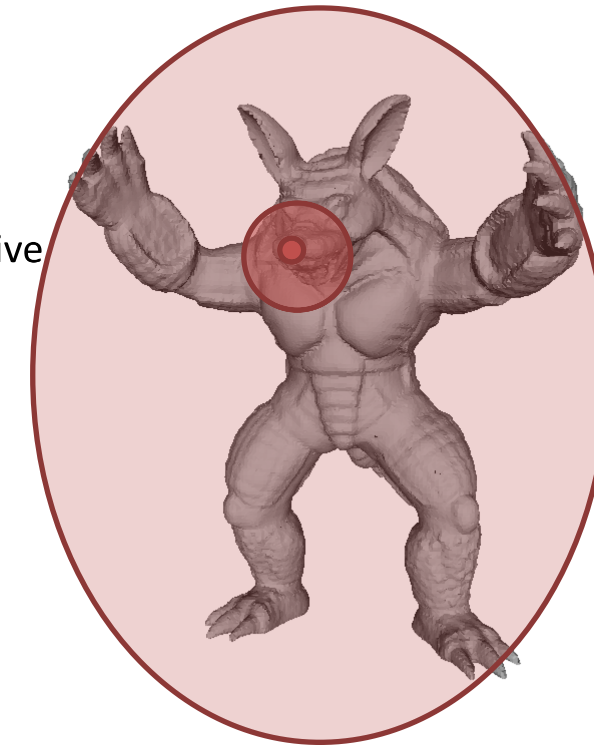


LRF: example

```
pcl::PointCloud< pcl::ReferenceFrame >::Ptr lrfs(new
       pcl::PointCloud< pcl::ReferenceFrame> ());

pcl::BOARDLocalReferenceFrameEstimation<pcl::PointXYZ, pcl::Normal,
pcl::ReferenceFrame> lrf_est;

lrf_est.setRadiusSearch (0.5f);
lrf_est.setInputCloud (keypoints);
lrf_est.setInputNormals (cloud_normals);
lrf_est.setSearchSurface (cloud);

lrf_est.compute (*lrfs);
```

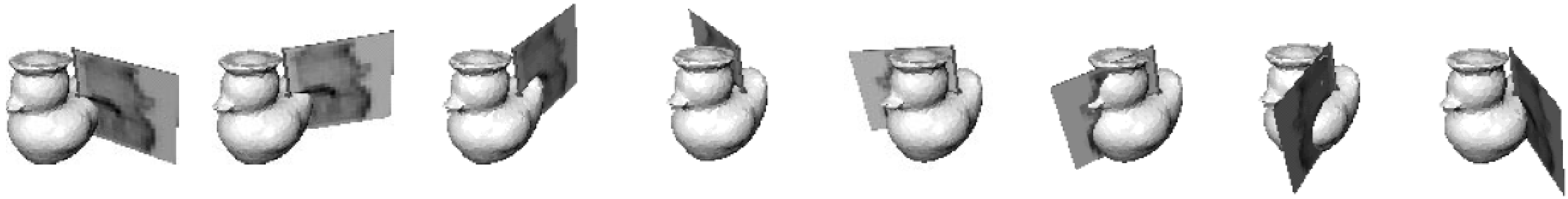
Global vs local representations

- **compact** representations aimed at detecting similarities between surfaces (*surface matching*)
- based on the support size
  - **Pointwise descriptors**
    - Simple, efficient, but not robust to noise, often not descriptive enough
  - **Local/Regional descriptors**
    - Well suited to handle clutter and occlusions
    - Can be vector quantized in codebooks
    - Segmentation, registration, recognition in clutter, 3D SLAM
  - **Global descriptors**
    - Complete information concerning the surface is needed (no occlusions and clutter, unless pre-processing)
    - Higher invariance, well suited for **retrieval and categorization**
    - More descriptive on objects with poor geometric structure (household objects..)



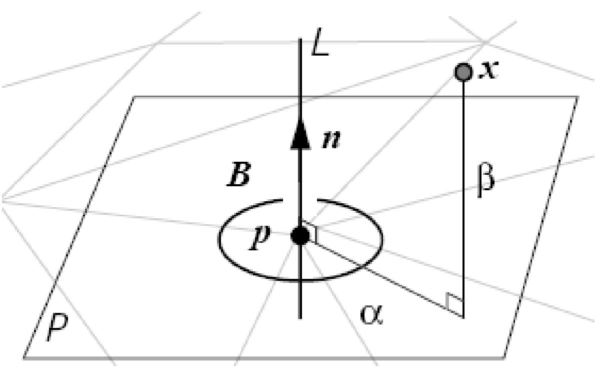
Spin Images

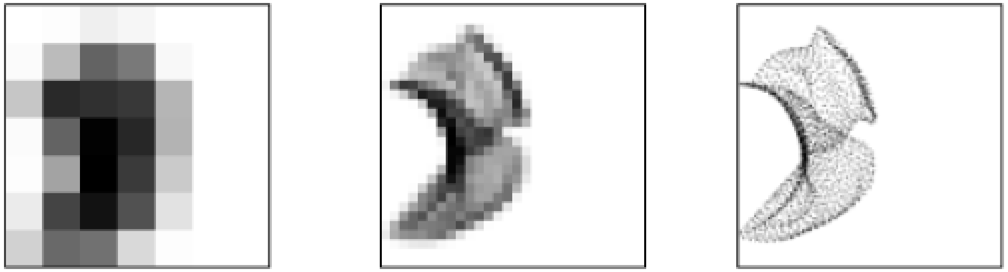
- Spin Image descriptor [Johnson99] is arguably the most popular 3D local descriptor
- 2D histograms accumulating points by spinning around a repeatable axis (*normal*)



(courtesy of Johnson & Hebert)

- Rotation and translation invariant, not scale invariant
- Appreciates uniform surface sampling
- Variants: compressed-SI (PCA)
- ***pcl::SpinImageEstimation***





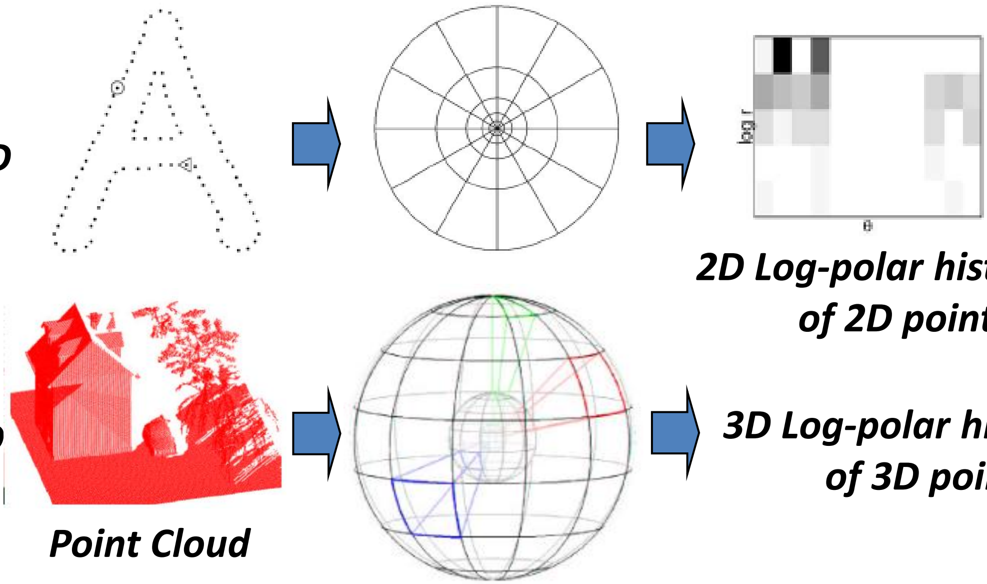
Effect of bin size (courtesy of Johnson & Hebert)

3D/Unique Shape Contexts

- ***3DSC*** [Frome ECCV04]: extension of the Shape Contexts approach [Belongie et al. PAMI02] to the 3D domain (***pcl::ShapeContext3DEstimation)***
- Each point is accumulated in the 3D bin it falls in, being weighted proportionally to the local point cloud density around the bin and to the bin volume
- No unique local Reference Frame -> L descriptions for each feature (*L: number of azimuth bins*)

2D

3D



Point Cloud

2D Log-polar histogram of 2D points

3D Log-polar histogram of 3D points

- **Unique Shape Context (*USC*)** [Tombari 3DOR10]: a unique local RF is plugged in to orient univocally the 3D grid (***pcl::UniqueShapeContext)***
- Hence, only one description is needed for each feature point, decreasing the number of possible mismatches (spurious correspondences) during the matching stage.

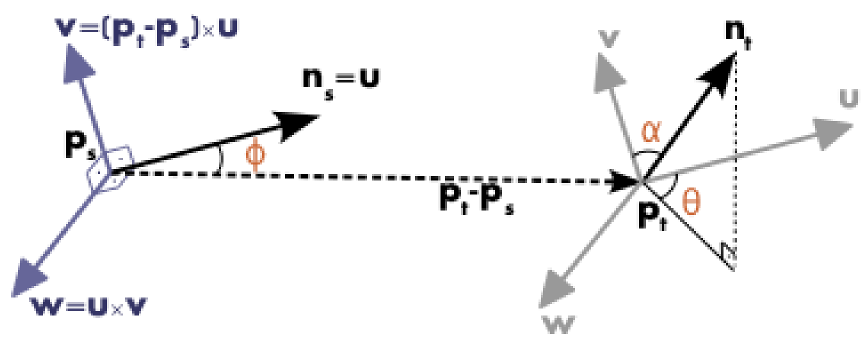
Point Feature Histogram

- PFH [Rusu08] computes 3 values for each pair in the neighbourhood
  - Complexity O(k^2), extremely slow.
- ***pcl::PFHEstimation***
- For each pair, it computes a LRF *u*-*v*-*w* centred on one point p_s as
  - The normal $u = n_s$
  - The cross product between ns and the vector (pt-ps) $v = n_s \times (p_t - p_s)$
  - The cross product between the previous vectors $w = u \times v$
- Then, it computes and accumulates

$$\alpha = \arccos(v \cdot n_t)$$

$$\phi = \arccos\left(u \cdot \frac{(p_t - p_s)}{\|p_t - p_s\|_2} \right)$$

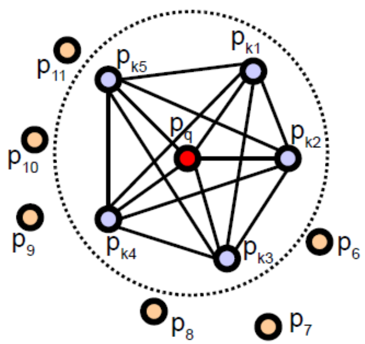
$$\theta = \arctan(w \cdot n_t, u \cdot n_t)$$

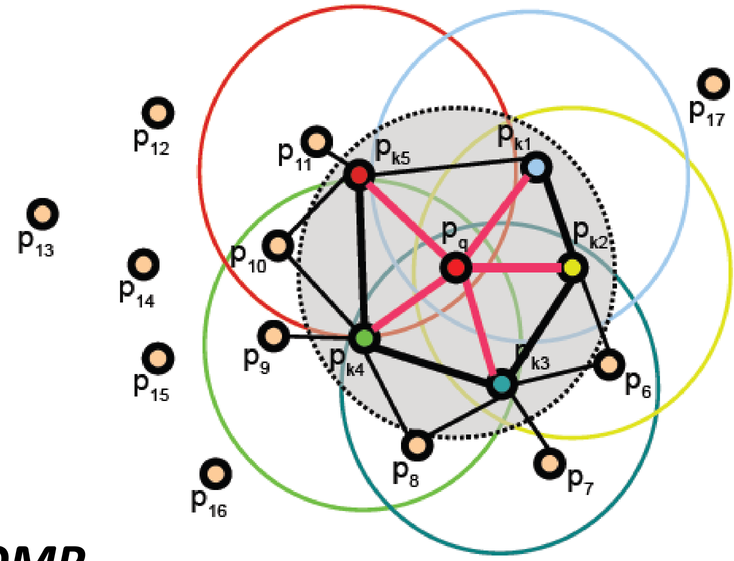


Fast PFH

- FPFH [Rusu09]: approximation of PFH with linear complexity in the number of neighbors
  - Compute SPFH (Simplified PFH) between the keypoint and every neighbor
  - Combine the weighted SPFHs to form the final Fast PFH

$$FPFH(p_i) = SPFH(p_i) + \frac{1}{k}\sum_{j=1}^{k}\frac{1}{\omega_j} SPFH(p_j)$$





- ***pcl::FPFHEstimation, pcl::FPFHEstimationOMP***

SHOT descriptor

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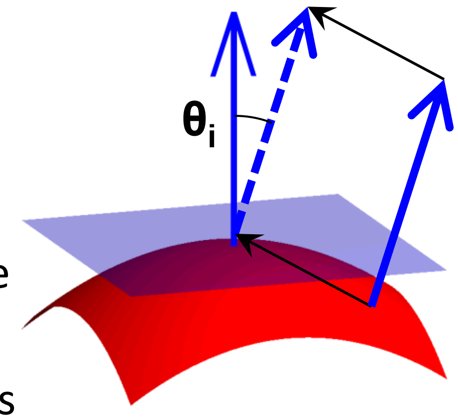
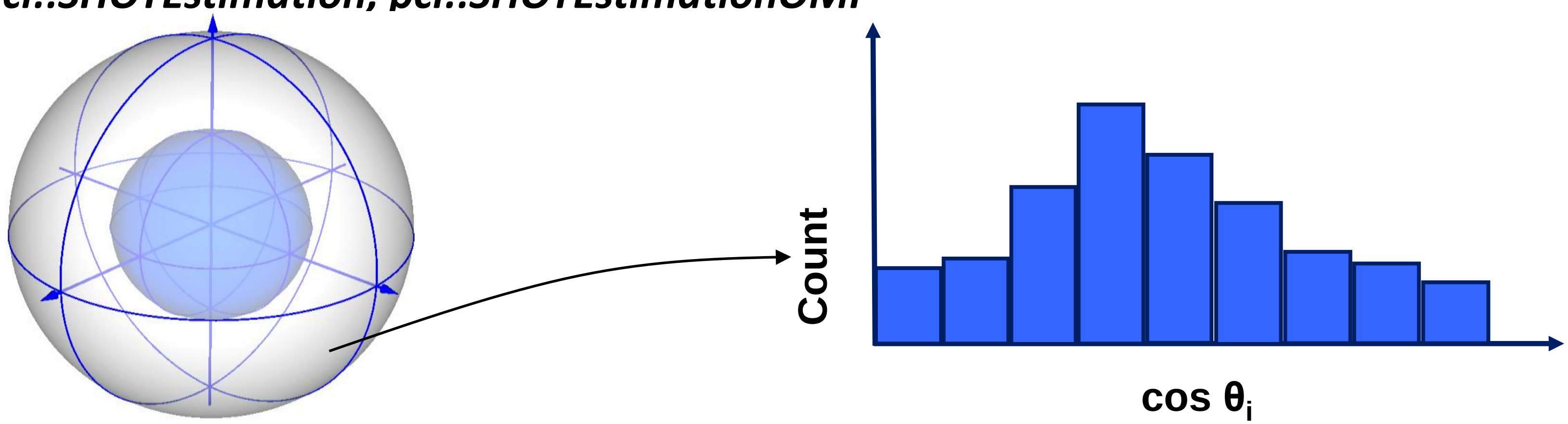
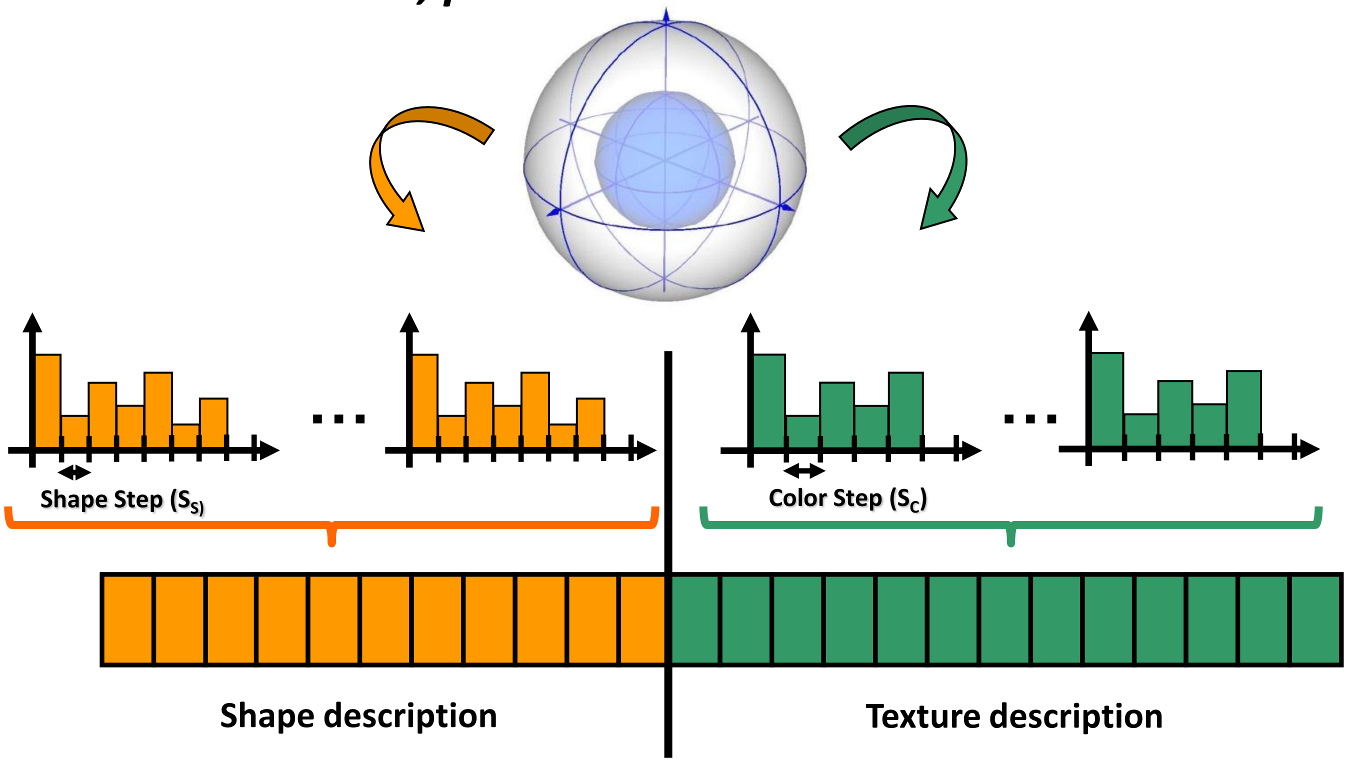
- Signatures of Histograms of OrienTations [Tombari10]
- Inspired by SIFT: computation of a geometric coarsely localized local set of histograms of first-order derivatives.
- The local support is partitioned by means of a spherical grid
- For each volume of the grid, an histogram of the cosines of the angle θi between the normal at each point and the normal at the feature point is computed.
- Quadrilinear interpolation to smooth out quantization distortions
- Normalization of the descriptor for robustness towards point density variations
- ***pcl::SHOTEstimation, pcl::SHOTEstimationOMP***





SHOT for RGB-D data

- SHOT for RGB-D data [Tombari11] deploys
  - Shape, as the SHOT descriptor
  - Texture, as histograms in the *Lab* space
  - Pairs of *Lab* triplets (center point and its neighbor) can be compared using specific metrics (CIE94, CIE2000, ..), although the L1-norm proved to be a good trade-off
- ***pcl::SHOTColorEstimation, pcl::SHOTColorEstimationOMP***



Code Example: descriptors

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```
pcl::PointCloud<pcl::SHOT352>::Ptr descriptors (new
        pcl::PointCloud<pcl::SHOT352>());

pcl::SHOTEstimationOMP<PointType, NormalType, DescriptorType> describer;

describer.setRadiusSearch (support_radius);
describer.setInputCloud (keypoints);
describer.setInputNormals (normals);
describer.setSearchSurface (cloud);

describer.compute (*descriptors);
```

Summing up..

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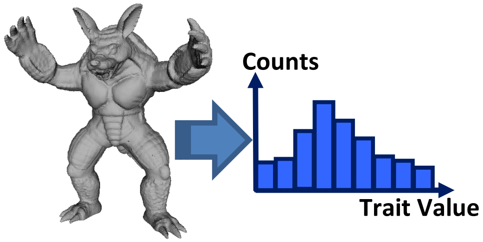
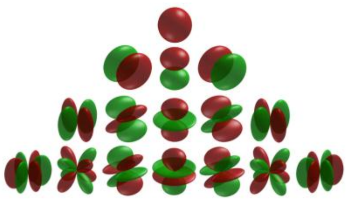
Method	Category	Unique LRF	Texture
Struct. Indexing [Stein92]	Signature	No	No
PS [Chua97]	Signature	No	No
3DPF [Sun01]	Signature	No	No
3DGSS [Novatnack08]	Signature	No	No
KPQ [Mian10]	Signature	No	No
3D-SURF [Knopp10]	Signature	Yes	No
SI [Johnson99]	Histogram	RA	No
LSP [Chen07]	Histogram	RA	No
3DSC [Frome04]	Histogram	No	No
ISS [Zhong09]	Histogram	No	No
USC [Tombari10]	Histogram	Yes	No
PFH [Rusu08]	Histogram	RA	No
FPFH [Rusu09]	Histogram	RA	No
Tensor [Mian06]	Histogram	No	No
RSD [Marton11]	Histogram	RA	No
HKS [Sun09]	Other	-	No
MeshHoG [Zaharescu09]	Hybrid	Yes	Yes
SHOT [Tombari10]	Hybrid	Yes	Yes

Global descriptor taxonomy

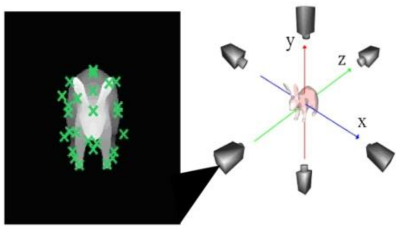
- Taxonomy for global descriptors [Akgul09]
- **Histogram-based:** accumulators of local or global features
  - Robustness, paid off with less descriptivness
  - Shape Distributions [Osada02], 3D Shape Histograms [Ankerst99], Orientation Histograms [Horn84], **Viewpoint Feature Histogram (VFH) [Rusu10]**, **Clustered-VFH** [Aldoma11], **OUR-CVFH [Aldoma12]**



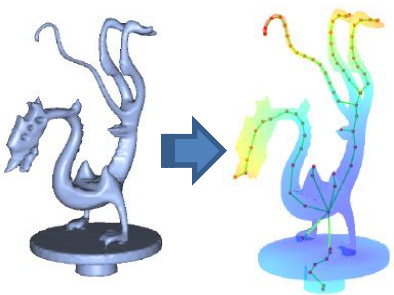
- **Transform-based:** Transform geometric information in a domain where representation is compact and invariant
  - Compact descriptors by retaining only a subset of (eg. the first) coefficients
  - 3D Fourier Transform [Dutagaci05], Angular Radial Tr. [Ricard05], 3D Radon Tr. [Daras04], Spherical Harmonics [Kazhdan03], wavelets [Laga06]



- **2D view-based:** 3D surface is transformed into a set of 2D projections (range maps)
  - 2D image descriptors are computed on each 2D view
  - Fourier descriptors [Vranic 04], Zernike moments [Chen03], SIFT [Ohbuchi08], SURF, ..

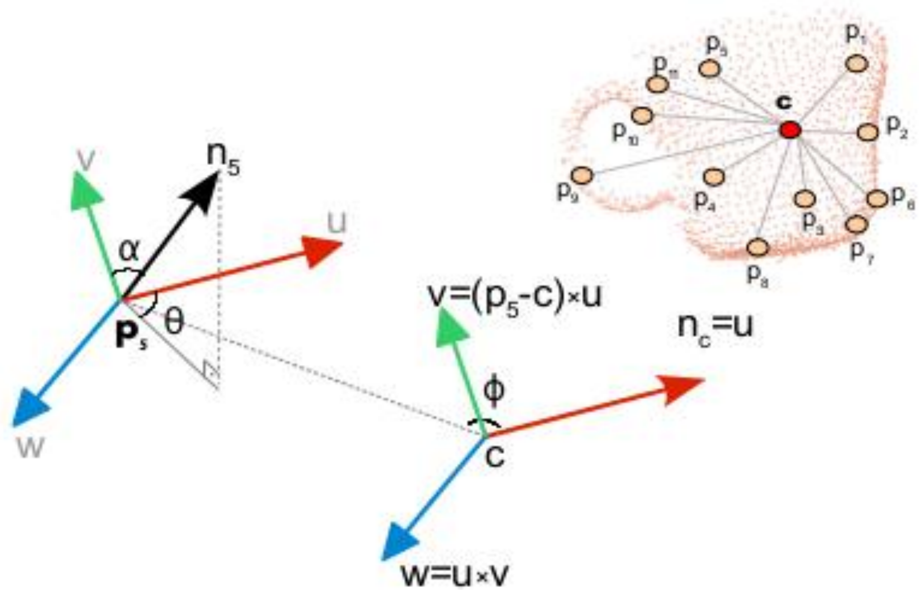


- **Graph-based:** A graph is built out of the surface
  - Transform the graph into a vector-based numerical description
  - topology-based[Hilaga01], Reeb graph[Tung05], skeleton-based[Sundar03]



VFH

- Viewpoint Feature Histogram [Rusu 10]
  - Each 3D model is rendered into different views
  - Each view provides one descriptor
    - Explicitly encodes the viewpoint from where the surface was captured/sensed
  - Based on Point Feature Histogram (PFH)
  - For each point pair ***(pi, pc)***:
    - Compute a LRF for the **centroid**
      - $u = n_c$
      - $v = \frac{p_i - p_c}{\|p_i - p_c\|} \times u$
      - $w = u \times v$
    - $\alpha = arccos(v \cdot n)$
    - $\phi = arccos\left(u \cdot \frac{p_i - p_c}{\|p_i - p_c\|}\right)$
    - $\theta = atan2(w \cdot n, u \cdot n)$

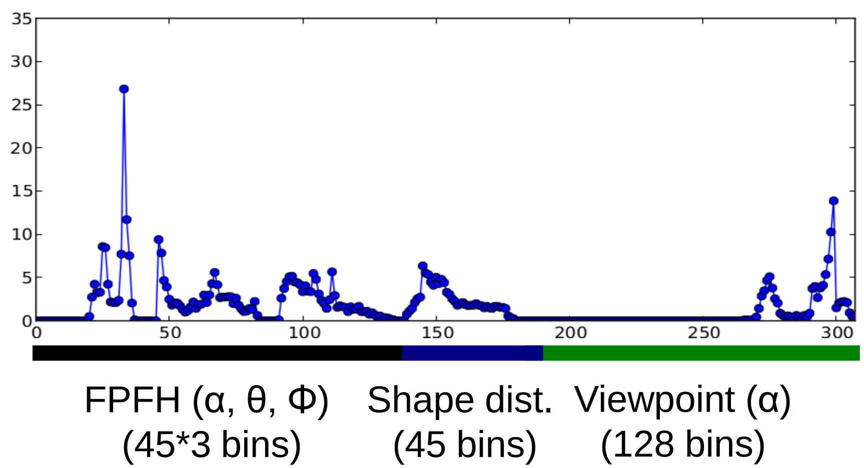


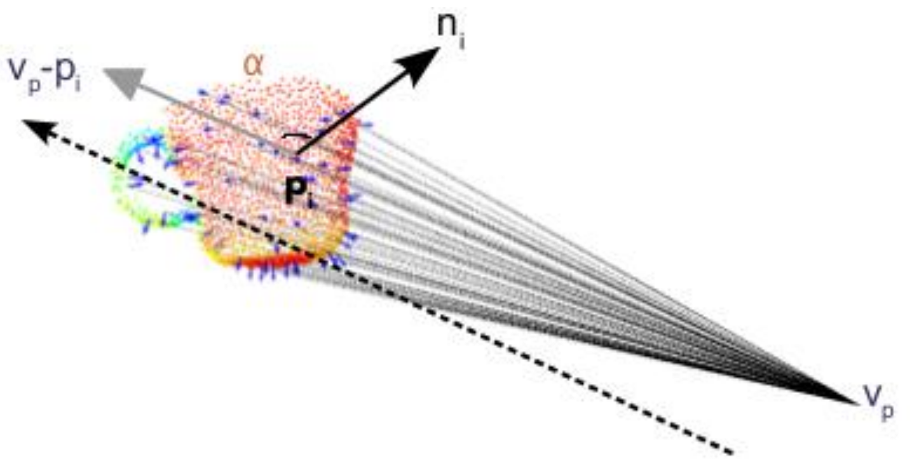
VFH (2)

- Descriptor is built with:
  - 3 “PFH” angular values (α, θ, Φ) wrt. centroid (45 bins each)
  - 1 shape distribution-like component wrt. centroid (45 bins):

$$SDC = \frac{(p_c - p_i)^2}{max\left((p_c - p_i)^2\right)}$$

  - 1 angular value (angle between normal and central view direction – α) (128 bins)

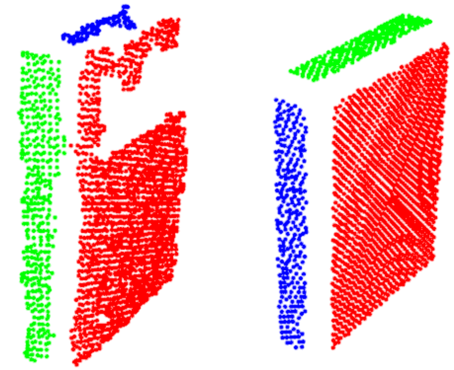




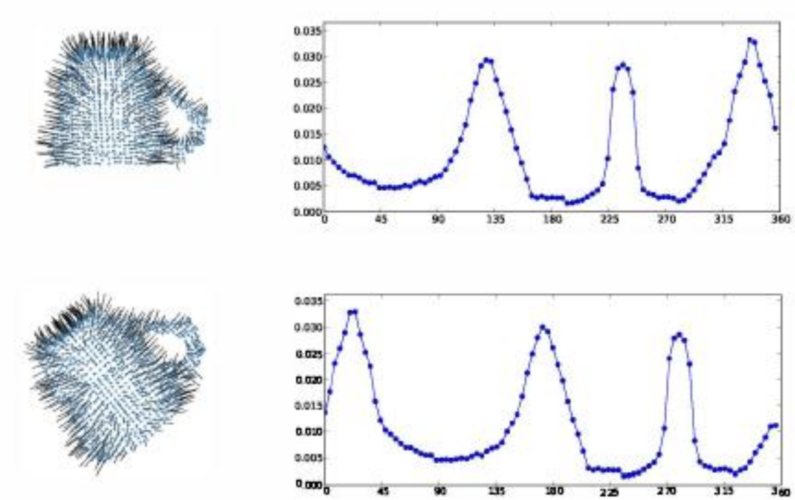
- ***pcl::VFHEstimation***

CVFH

- The reference frame from VFH is sensitive to missing parts in the surface
- Clustered VFH (CVFH) [Aldoma 11]
  - Perform a further smooth region segmentation on each view
  - Apply a VFH descriptor on each connected component (*cluster*) – no normalization to encode the real size of the object

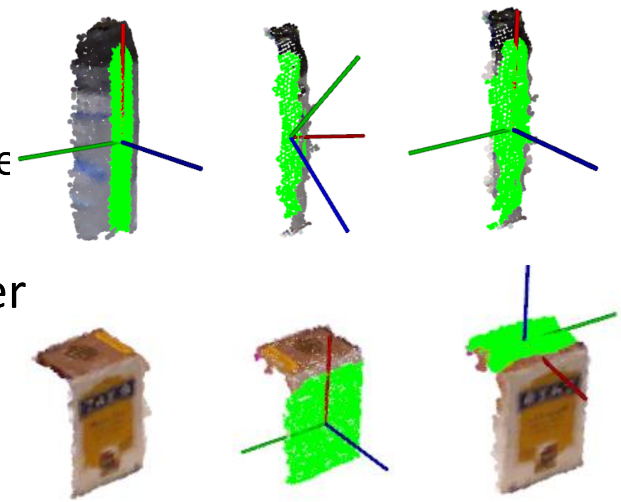


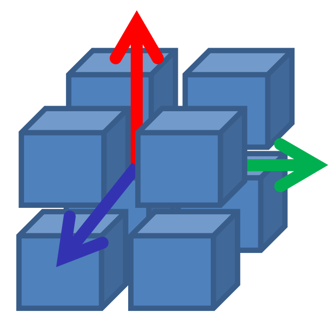
- VFH, CVFH et al. still present invariance (ambiguity) on the roll angle
- **Camera Roll Histogram** to determine a full 6DO pose
  - distribution of normal angles of all points projected on the camera plane
  - «shift» along roll angle computed by matching CRHs
- ***pcl::CVFHEstimation***



OUR-CVFH

- Improvement [Aldoma DAGM13] to CVFH with
  - More robust to missing data
  - A descriptor for each smooth region composing the descriptor)
- One Local-Global Reference Frame for each cluster
  - Locally: compute principal directions
  - Globally: sign disambiguation
- RF splits space in octants:
  - For each octant, Shape distribution (D1) (13 bins)
- Final descriptor:
  - Octant-based shape dist. and color hist.
  - “Global” normal distribution (CVFH) (45x3 els.)
  - Viewpoint (CVFH) (64 els.) (half wrt. VFH/CVFH)
  - Overall size: 13x8 + 199 = 303
- ***pcl::OURCVFHEstimation*** (currently only trunk)





Descriptor matching

Keypoint Extraction → Description → **Matching**

- Problem: find the kNN of a n-dimensional query vector **q** within a set of m candidates (same size)
  - Variant: find all neighbors within an hypersphere of radius **r** centered on **q**
- To speed up the brute force, fast indexing schemes
  - Kd-tree [Freidman77]
  - Hierarchical k-means tree [Fukunaga75]
  - Locality Sensitive Hashing (LSH) [Andoni06]
- Kd-tree slows down at high dimensions (too many nodes, long exploration time), need for approximate kd-tree search
  - Best Bin First [Beis97]
  - Randomized kd-tree [Silpa-Anan08]
  - FLANN [Muja09]
- Example: **`pcl::KdTreeFLANN<pcl::SHOT352> matcher`**; (in *pcl_kdtree* module)

  (also have a look at **`pcl::search::FlannSearch`**)

Acknowledgements

- Thanks to: Samuele Salti, Aitor Aldoma