SAPIENZA
UNIVERSITÀ DI ROMA

Elective in A.I. - Robot Programming

2014/2015 - Prof: Daniele Nardi

Perception with RGB-D sensors – Jacopo Serafin

Point Cloud Library (PCL), Surface Normals, Generalized ICP

Contact

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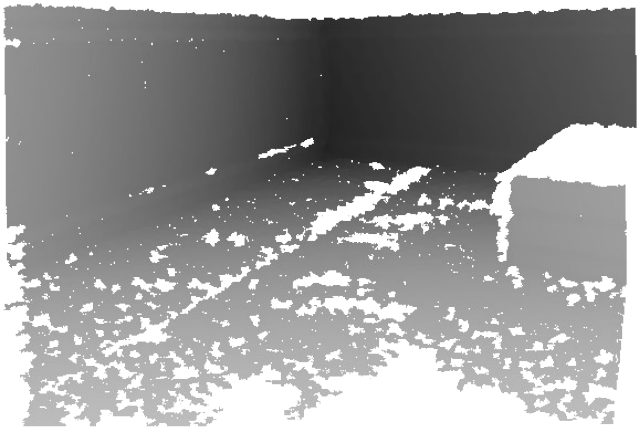
Organized Point Cloud

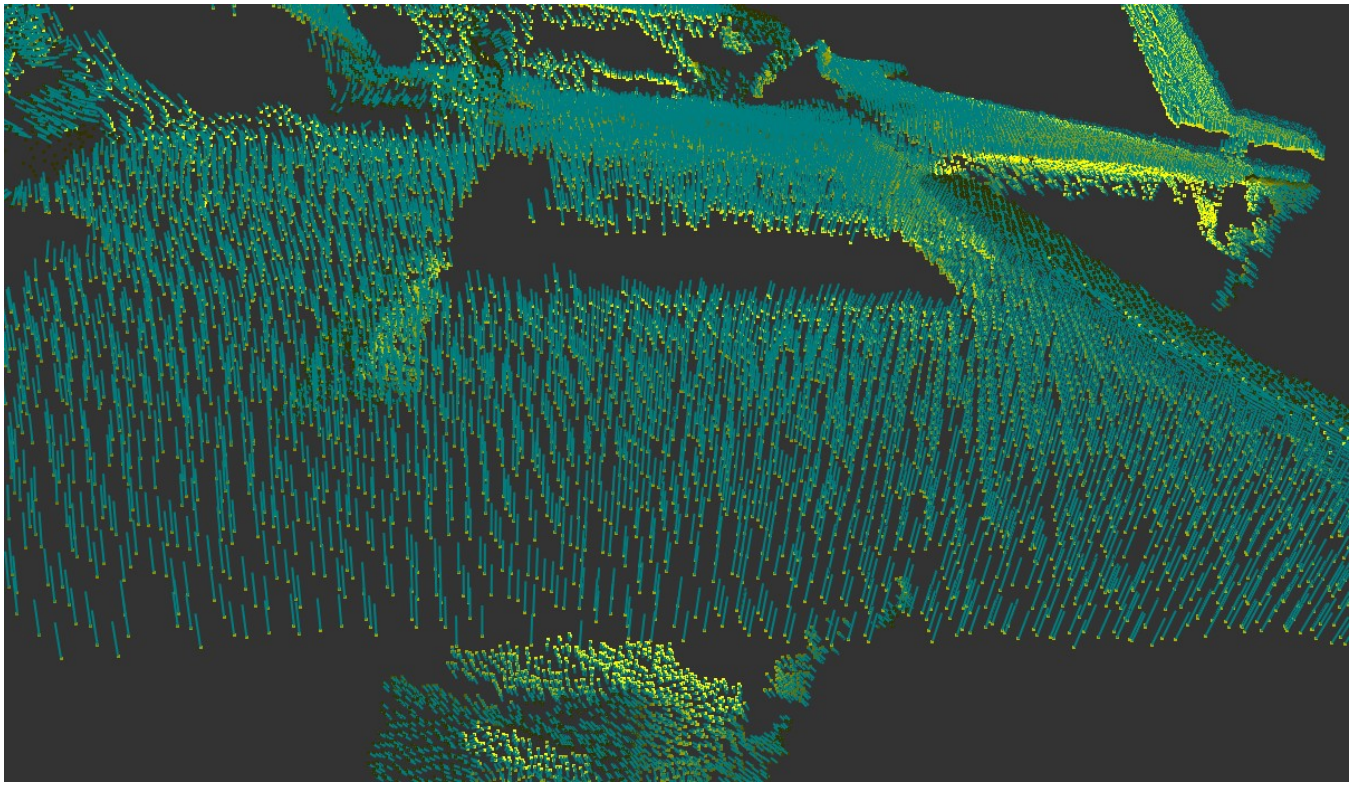
- Goal: maintain same structure (rows and columns) of the depth image
- Necessary for many algorithms that suppose to have an organized point cloud
- Depth images contain not valid values (e.g. zero pixels), thus the cloud is not dense



```
/* Image-like organized structure,
with 640 rows and 480 columns */

cloud.width = 640;

/* thus 640*480=307200 points total
in the dataset */

cloud.height = 480;
```

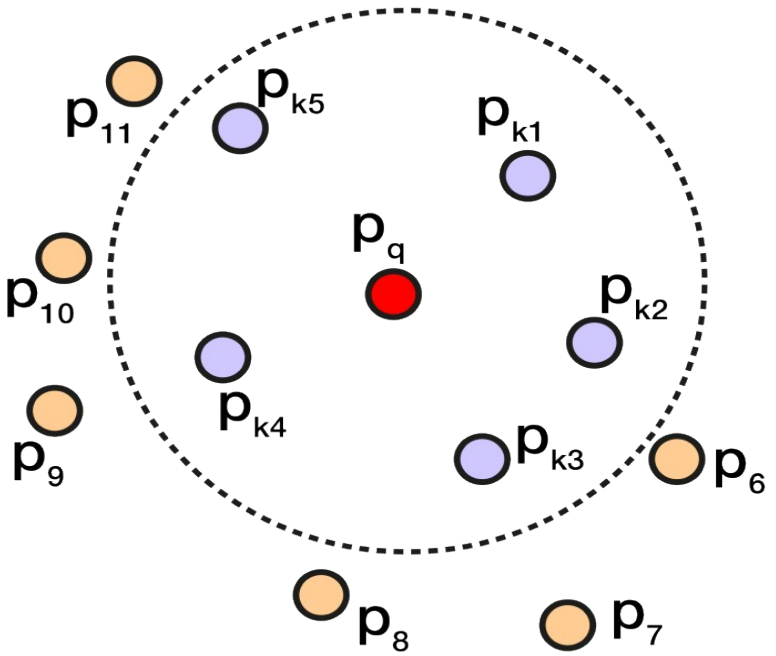
Surface Normal

- Vector normal to the surface where the point lies
- Provide additional information about the structure around the point



How to Compute the Surface Normals

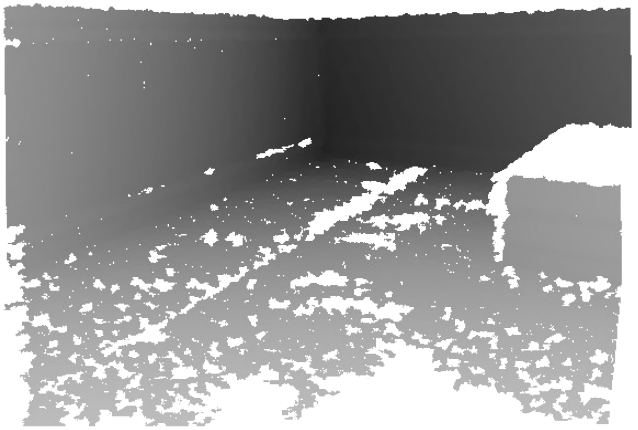
- Approximate the neighborhood of a point with a surface:
  - Compute the covariance matrix
  - Compute singular value decomposition
  - Take the normal as the eigenvector associated to the smallest eigenvalue

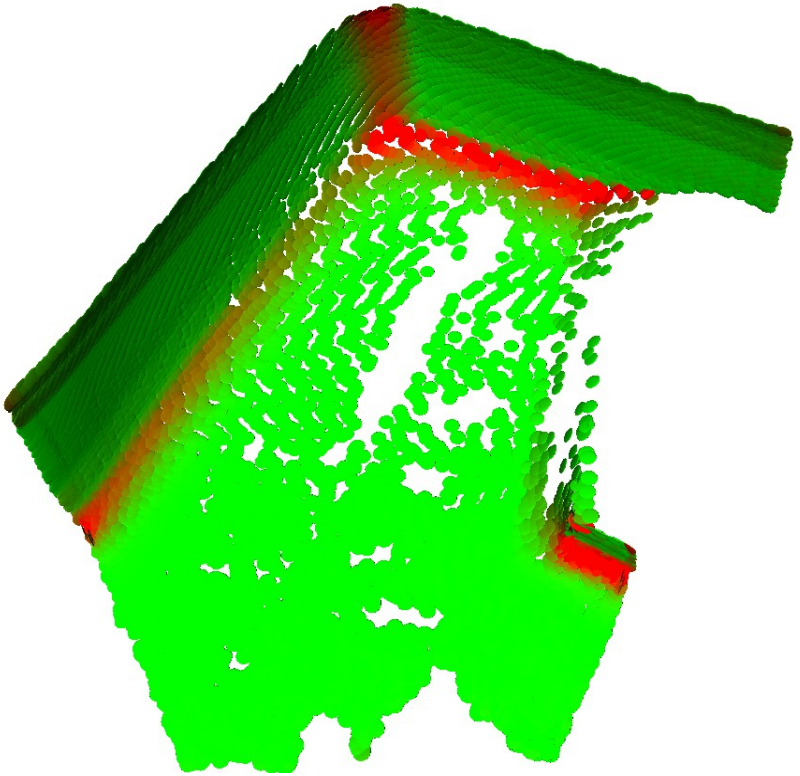


Curvature

- Can be computed as a function of the eigenvalues of the covariance matrix:

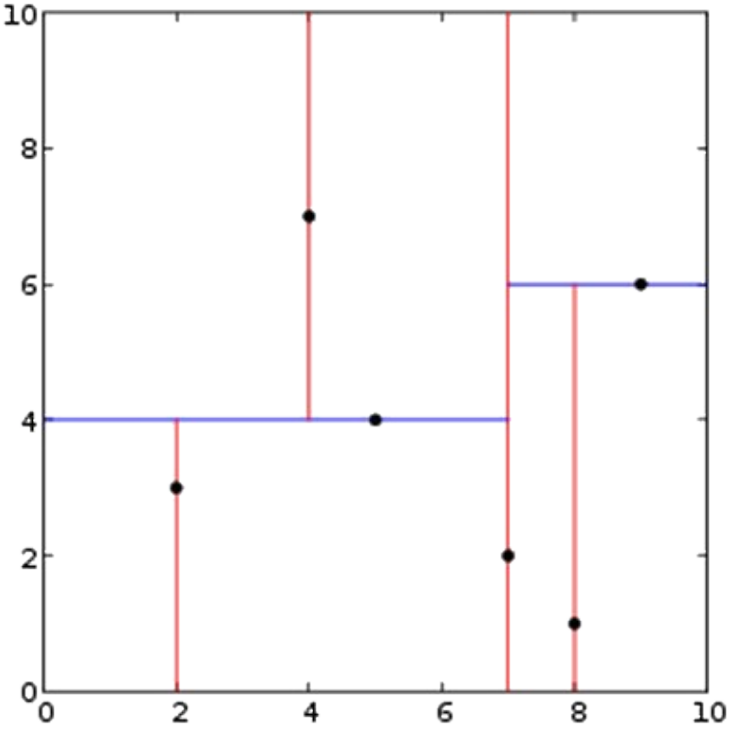
$$\sigma = \lambda_0 / (\lambda_0 + \lambda_1 + \lambda_2) \in [0,1]$$





KdTree

- Data structure to organize points in a space with k dimensions
- Very useful for range and nearest neighbor searches
- Cost for search one nearest neighbor is equal to O(log n)



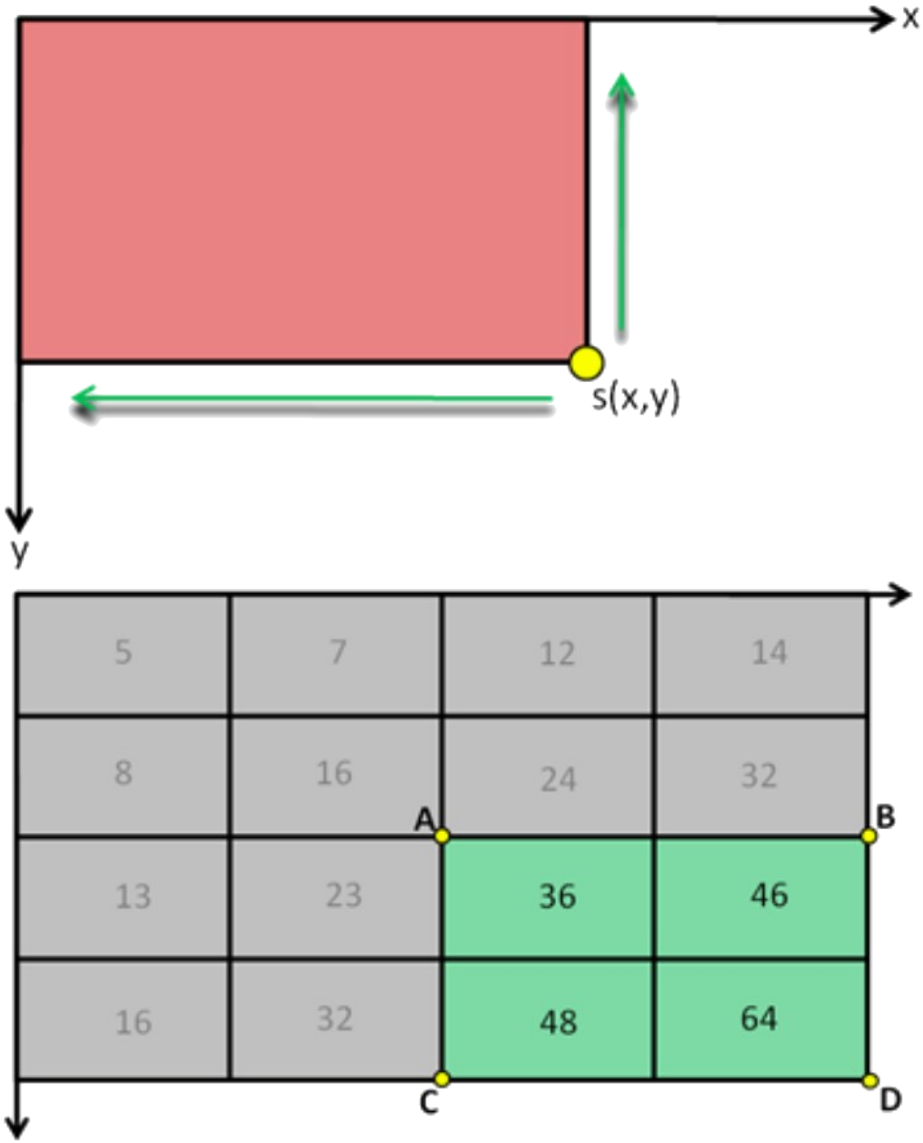

```
pcl::KdTreeFLANN<pcl::PointXYZ> kdtree;

kdtree.setInputCloud (cloud);

// K nearest neighbor search
kdtree.nearestKSearch (searchPoint, K,
                       pointIdxNKNSearch,
                       pointNKNSquaredDistance);

// Neighbors within radius search
kdtree.radiusSearch (searchPoint, radius,
                     pointIdxRadiusSearch,
                     pointRadiusSquaredDistance);
```

Surface Normals Computation: KdTree Based Code

```
// Create the normal estimation class, and give it the input dataset
pcl::NormalEstimation<pcl::PointXYZ, pcl::Normal> ne;
ne.setInputCloud (cloud);

// Create an empty kdtree, and pass it to the normal estimation object
pcl::search::KdTree<pcl::PointXYZ>::Ptr tree (new
pcl::search::KdTree<pcl::PointXYZ> ());
ne.setSearchMethod (tree);

// Output datasets
pcl::PointCloud<pcl::Normal>::Ptr cloud_normals (new
pcl::PointCloud<pcl::Normal>);

// Use all neighbors in a sphere of radius 3cm
ne.setRadiusSearch (0.03);

// Compute the features
ne.compute (*cloud_normals);
```

Integral Image

- It is a particular image where each pixel contains the sum of the pixels of the upper left part of the image
- Allows fast computation of the surface normals
- Once the integral image the cost for a surface normal computation is constant O(1)
- The main drawback is a loss of precision in the neighbors computation
- s(A, B, C, D) = s(A) + s(D) – s(B) - s(C)

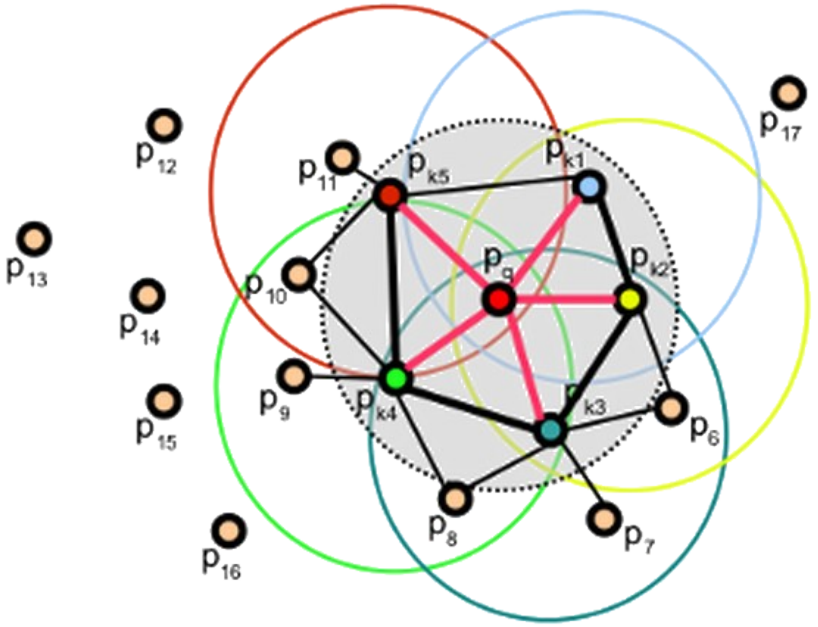


Surface Normals Computation: Integral Images Based Code

```
// estimate normals
pcl::PointCloud<pcl::Normal>::Ptr normals (new
pcl::PointCloud<pcl::Normal>);

// create a surface normals integral image estimator object
pcl::IntegralImageNormalEstimation<pcl::PointXYZ, pcl::Normal> ne;

// set some parameters
ne.setNormalEstimationMethod (ne.AVERAGE_3D_GRADIENT);
ne.setMaxDepthChangeFactor(0.02f);
ne.setInputCloud(cloud);

// compute the surface normals
ne.compute(*normals);
```

Fast Point Features Histograms (FPFH)

- Encode the point's k-neighborhood geometrical properties
- Fast computation allowing real-time execution

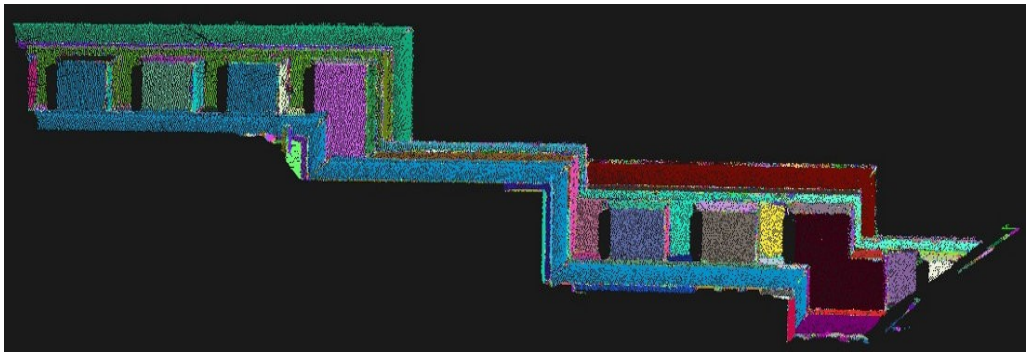


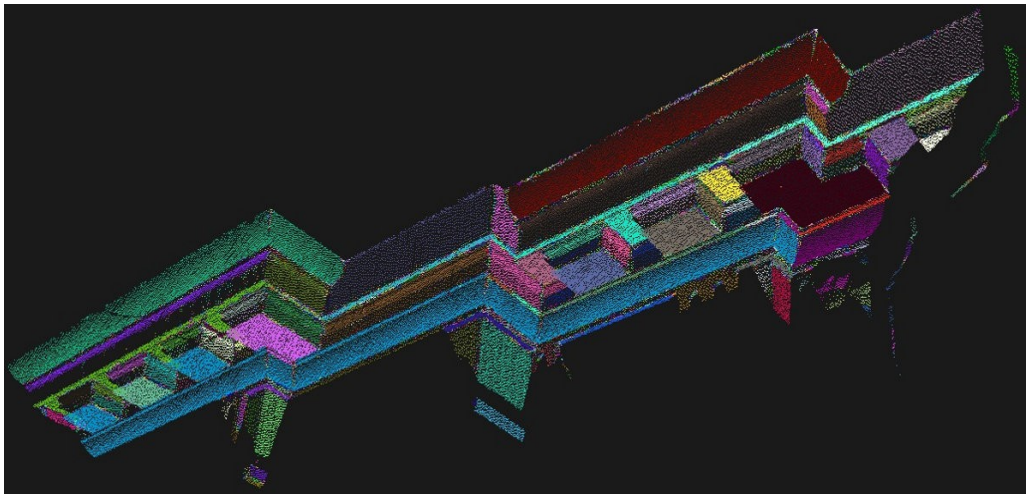
Fast Point Features Histograms (FPFH): Code

```
// Create the FPFH estimation class, and pass the input dataset + normals to it
pcl::FPFHEstimation<pcl::PointXYZ, pcl::Normal, pcl::FPFHSignature33> fpfh;
fpfh.setInputCloud (cloud);
fpfh.setInputNormals (normals);

// alternatively, if cloud is of tpe PointNormal, do fpfh.setInputNormals (cloud);
// Create an empty kdtree representation, and pass it to the FPFH estimation object.
// Its content will be filled inside the object, based on the given input dataset (as
// no other search surface is given).
pcl::search::KdTree<PointXYZ>::Ptr tree (new pcl::search::KdTree<PointXYZ>);

fpfh.setSearchMethod (tree);

// Output datasets
pcl::PointCloud<pcl::FPFHSignature33>::Ptr fpfhs (new
pcl::PointCloud<pcl::FPFHSignature33> ());

// Use all neighbors in a sphere of radius 5cm
// IMPORTANT: the radius used here has to be larger than the radius used to estimate
// the surface normals!!!
fpfh.setRadiusSearch (0.05);

// Compute the features
fpfh.compute (*fpfhs);
```

Region Growing Segmentation Based on Surface Normals

- Merge the points that are close enough in terms of smoothness constraints
- Until all the points not in a region are parsed:
  - Select a point as seed
  - Check recursively if its neighbors satisfy the constraints (angle difference between the surface normals):
    - If at least one, or more neighbors are good, add them to the region
    - If not, generate a new seed and create a new region



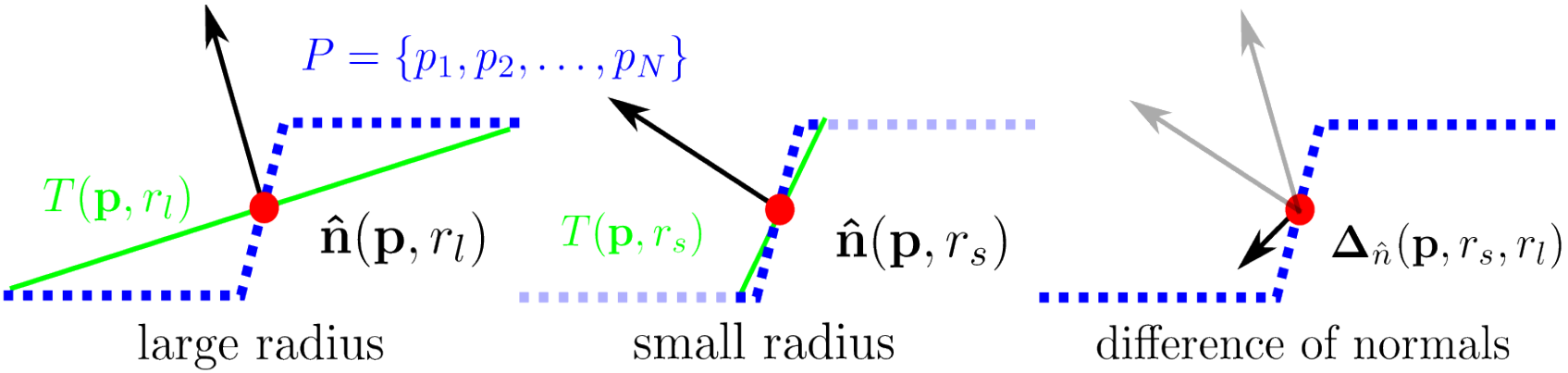


Region Growing Segmentation Based on Surface Normals: Code

```
// create the object that implements the surface normals region growing algorithm
pcl::RegionGrowing<pcl::PointXYZ, pcl::Normal> reg;

// Set some parameters
reg.setMinClusterSize (50);
reg.setMaxClusterSize (1000000);
reg.setSearchMethod (tree); // e.g. KdTree
reg.setNumberOfNeighbours (30);
reg.setInputCloud (cloud);
reg.setInputNormals (normals);
reg.setSmoothnessThreshold (3.0 / 180.0 * M_PI);
reg.setCurvatureThreshold (1.0);

// Perform the segmentation
std::vector <pcl::PointIndices> clusters;
reg.extract (clusters);

// Print some information
std::cout << "Number of clusters is equal to " << clusters.size () << std::endl;
std::cout << "First cluster has " << clusters[0].indices.size () << " points." << endl;
```

Difference of Normals for Segmentation

- Estimate the normals for every point using a large support radius r_l
- Estimate the normals for every point using a small support radius r_s
- Compute the normalized difference of normals for every point, as shown in the image
- Filter the resulting vector field to isolate points belonging to the scale/region of interest.

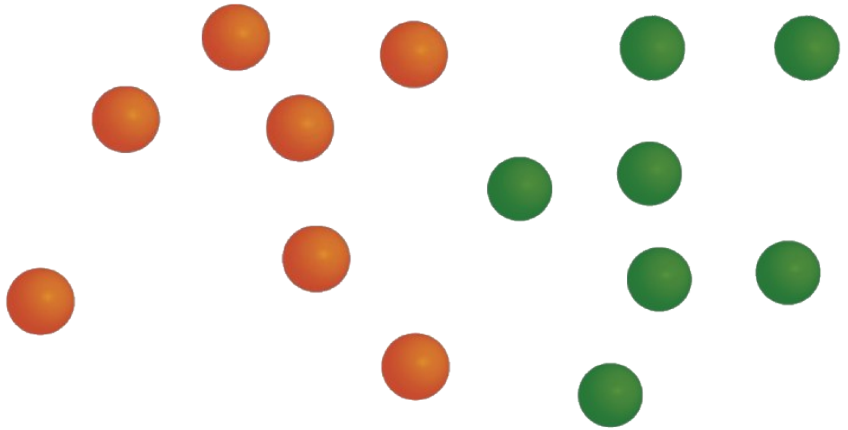


Difference of Normals for Segmentation: Code

```
// Create Difference of Normal operator
pcl::DifferenceOfNormalsEstimation<PointXYZRGB, PointNormal, PointNormal> don;

don.setInputCloud (cloud);
don.setNormalScaleLarge (normals_large_radius);
don.setNormalScaleSmall (normals_small_radius);

// Check possible failures
if (!don.initCompute ())
{
     std::cerr << "Error: Could not intialize DoN feature operator" << std::endl;
     exit (EXIT_FAILURE);
}

// Compute Difference of Normals
don.computeFeature (*doncloud);

// Filter by magnitude
...
```

Point Cloud Registration

We want to find the translation and the rotation that maximize the overlap between two point clouds



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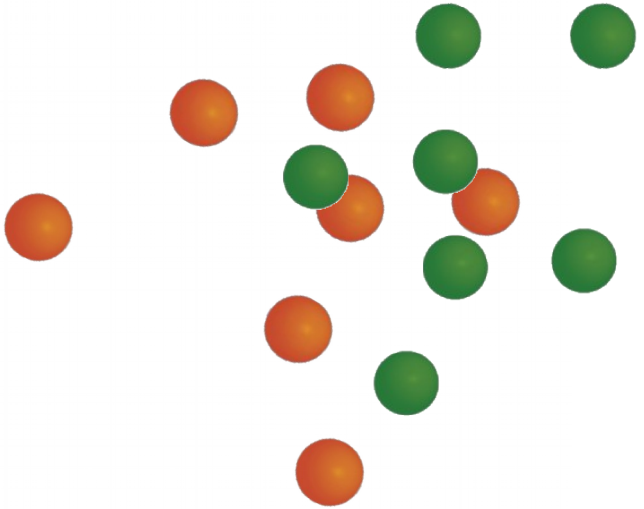

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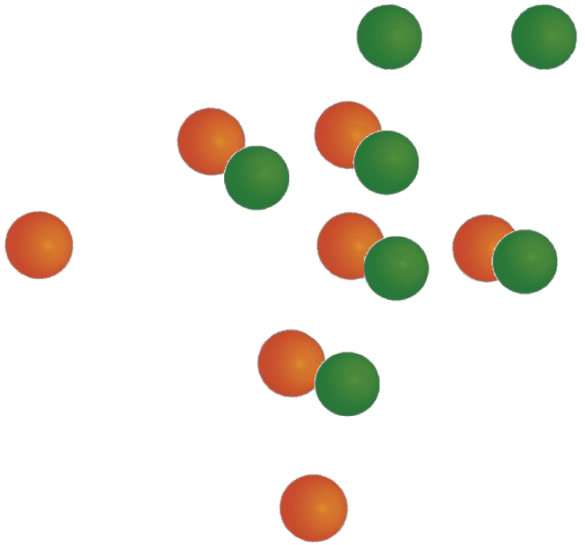

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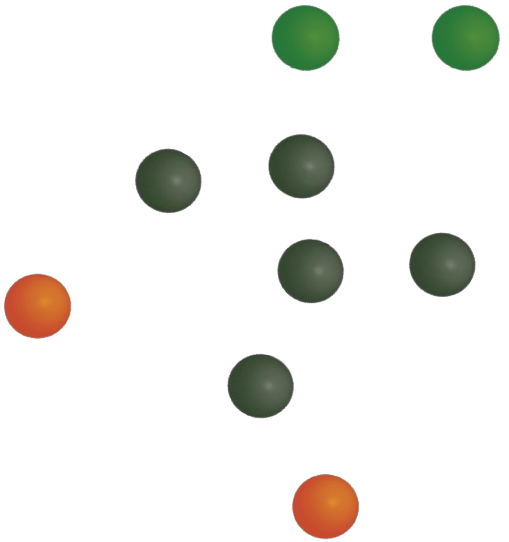
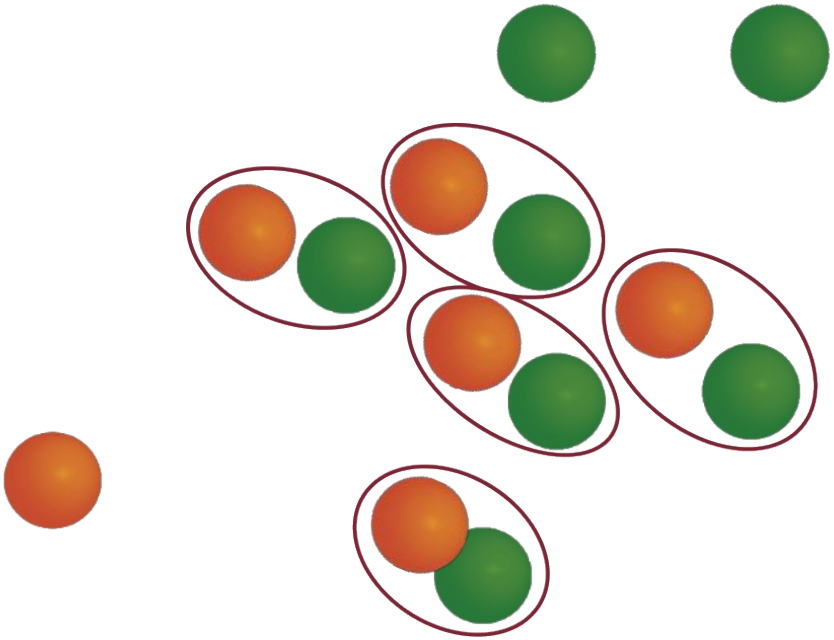


Iterative Closest Point Algorithm

ICP iteratively refine an initial transformation **T** by alternating:

- **search of correspondences between the two point clouds…**
- and the optimization step to update the current transformation



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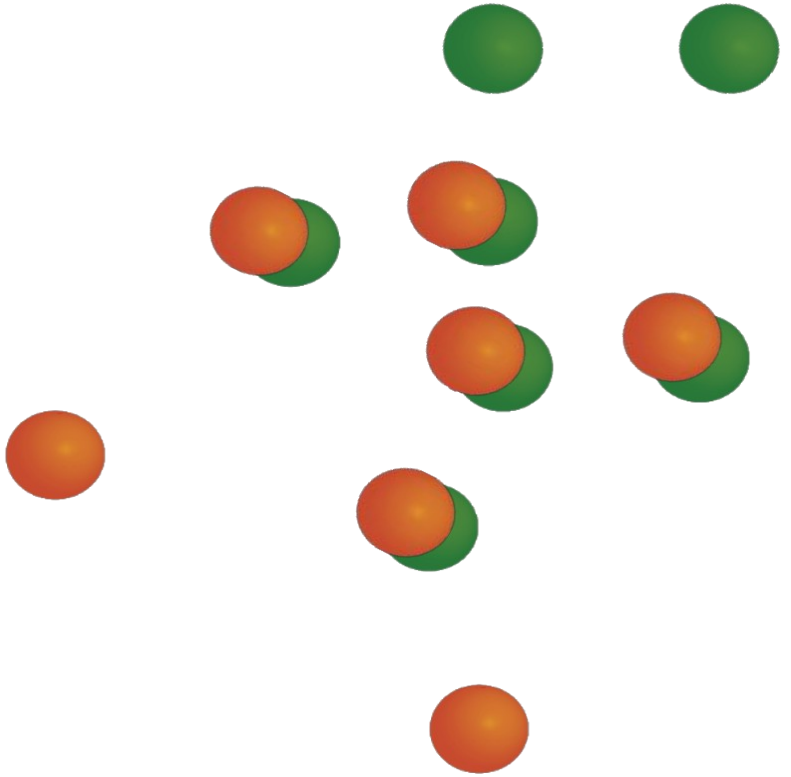
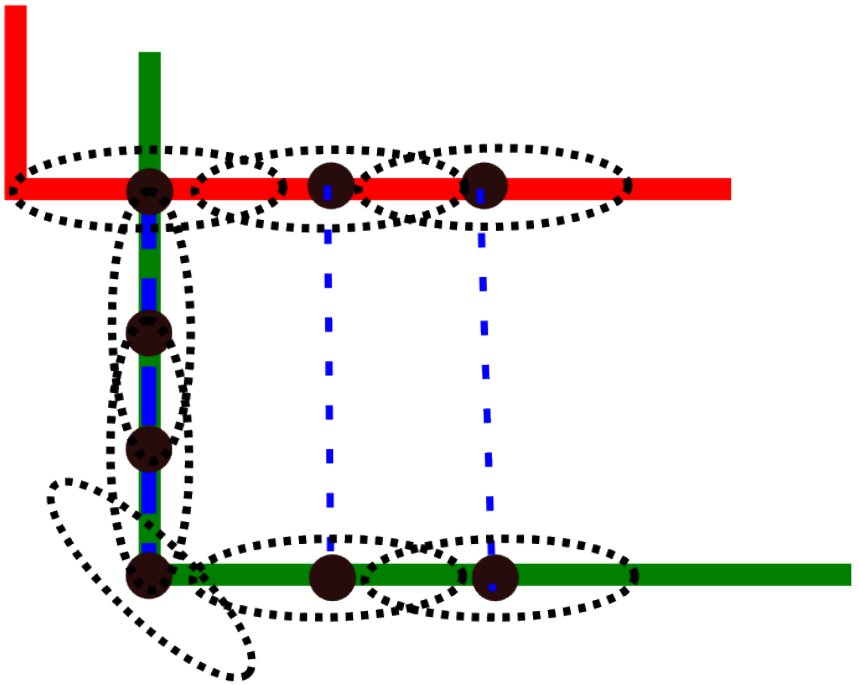


Point Cloud Registration: ICP Based Code

```
// create the object implementing ICP algorithm
pcl::IterativeClosestPoint<pcl::PointXYZ, pcl::PointXYZ> icp;

// set the input point cloud to align
icp.setInputCloud(cloud_in);
// set the input reference point cloud
icp.setInputTarget(cloud_out);

// compte the point cloud registration
pcl::PointCloud<pcl::PointXYZ> Final;
icp.align(Final);

// print fitness score
std::cout << "has converged:" << icp.hasConverged()
          << " score: "
          << icp.getFitnessScore() << std::endl;

// print the output transformation
std::cout << icp.getFinalTransformation() << std::endl;
```

Generalized ICP (GICP)

- Variant of ICP
- Assumes that points are sampled from a locally continuous and smooth surfaces
- Since two points are not the same it is better to align patches of surfaces instead of the points



Point Cloud Registration: GICP Based Code

```
// create the object implementing ICP algorithm
pcl::GeneralizedIterativeClosestPoint<pcl::PointXYZRGBNormal,
                                      pcl::PointXYZRGBNormal> gicp;

// set the input point cloud to align
gicp.setInputCloud(cloud_in);
// set the input reference point cloud
gicp.setInputTarget(cloud_out);

// compte the point cloud registration
pcl::PointCloud<pcl::PointXYZRGBNormal> Final;
gicp.align(Final);

// print if it the algorithm converged and its fitness score
std::cout << "has converged:" << gicp.hasConverged()
          << " score: "
          << gicp.getFitnessScore() << std::endl;

// print the output transformation
std::cout << gicp.getFinalTransformation() << std::endl;
```

Homework 1/3

Read a sequence of ordered pairs of images (RGB + Depth images) and save the associated point cloud with colors and surface normals on .pcd files (e.g. cloud_005.pcd)

- Download one of the datasets (e.g. desk_1.tar) at :

  http://rgbd-dataset.cs.washington.edu/dataset/rgbd-scenes/

Homework 2/3

After, for each file .pcd read sequentially:

- Align the current point cloud with the previous one by using Generalized ICP
- Save the cloud with its global transformation (either transforming directly the cloud or using the `sensor_origin` and `sensor_orientation` parameter provided in the point cloud object)

Homework 3/3

Apply a voxelization to the totoal point cloud (necessary to reduce the dimension in terms of bytes) and visualize it so that the entire scene reconstructed is shown

Hints

- Warning: the depth images are stored with 16 bit depth, so in this case calling the `cv::imread()` function you should specify the flag `CV_LOAD_IMAGE_ANYDEPTH` (or `-1`)
- WARNING: the input depth image should be scaled by a 0.001 factor in order to obtain distances in meters. You could use the opencv function:

```
input_depth_img.convertTo(scaled_depth_img, CV_32F, 0.001);
```

- As camera matrix, use the following default matrix:

```
float fx = 512, fy = 512, cx = 320, cy = 240;

Eigen::Matrix3f camera_matrix;

camera_matrix << fx, 0.0f, cx, 0.0f, fy, cy, 0.0f, 0.0f, 1.0f;
```

- As re-projection matrix, use the following matrix:

```
Eigen::Matrix4f t_mat;t_mat.setIdentity();

t_mat.block<3, 3>(0, 0) = camera_matrix.inverse();
```

Hints

- For each pixel (x,y) with depth d, obtain the corresponding 3D point as:

  ```
  Eigen::Vector4f point = t_mat * Eigen::Vector4f(x*d, y*d, d, 1.0);
  ```
  (the last coordinate of point can be ignored)

- WARNING: Since We are working with organized point clouds, also points with depth equal to 0 that are not valid, should be added to the computed cloud as `NaN`, i.e. in pseudocode:

  ```
  const float bad_point = std::numeric_limits<float>::quiet_NaN();
  if( depth(x, y) == 0) { p.x = p.y = p.z = bad_point; }
  ```

- To get the global transform of the current cloud just perform the following multiplication after you computed the registration:

  ```
  Eigen::Matrix4f globalTransform = previousGlobalTransform *
  alignmentTransform;
  ```

  `previousGlobalTransform` is the global transformation found for the previous point cloud

  `alignmentTransform` is the local transform computed using Generalized ICP

- WARNING: the first global transform has to be initialized to the identity matrix