pointcloudlibrary

PCL :: Segmentation

November 6, 2011

Outline

1. Model Based Segmentation
2. Plane Fitting Example
3. Normal Estimation
4. Polygonal Prism
5. Euclidean Clustering

RANSAC

If we know what to expect, we can (usually) efficiently segment our data:

RANSAC (Random Sample Consensus) is a randomized algorithm for robust model fitting.

Its basic operation:

1. select sample set
2. compute model
3. compute and count inliers
4. repeat until sufficiently confident

RANSAC

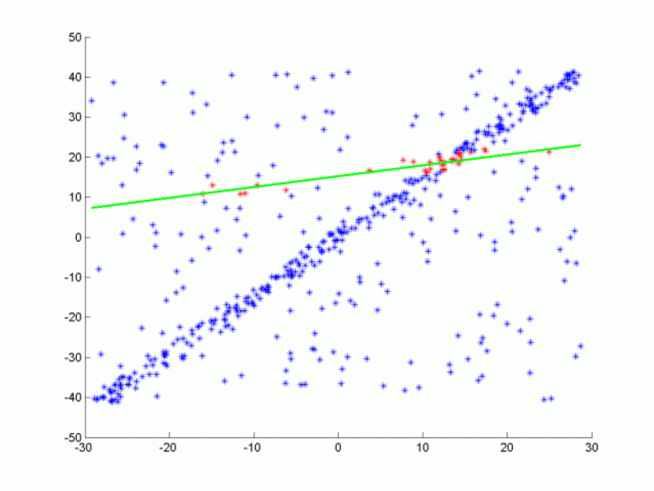
If we know what to expect, we can (usually) efficiently segment our data:

RANSAC (Random Sample Consensus) is a randomized algorithm for robust model fitting.

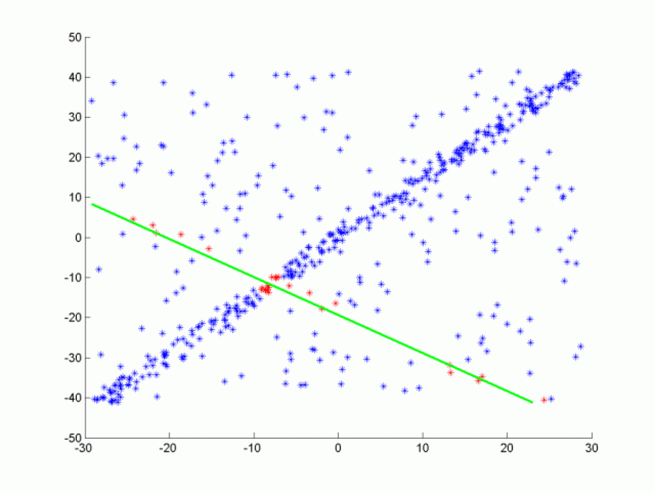
Its basic operation: line example

1. select sample set — 2 points
2. compute model — line equation
3. compute and count inliers — e.g. ϵ-band
4. repeat until sufficiently confident — e.g. 95%

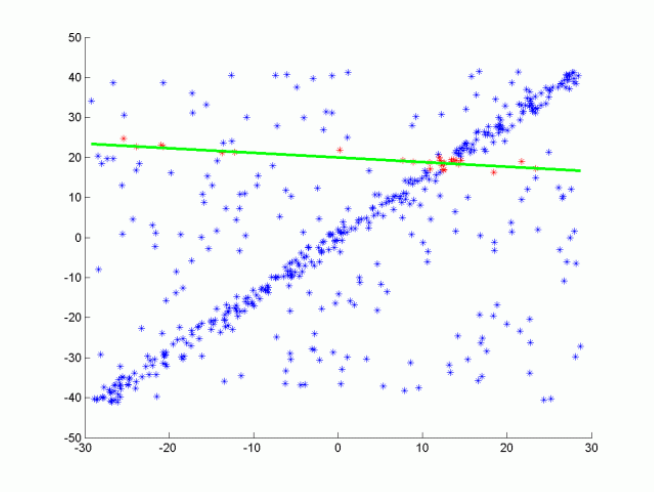
RANSAC



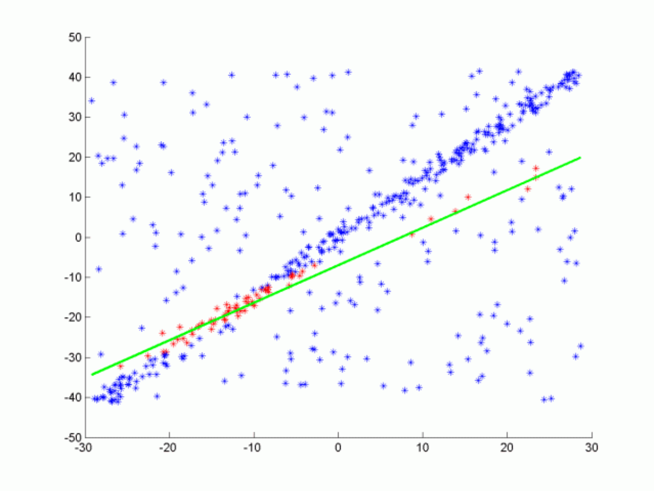
RANSAC



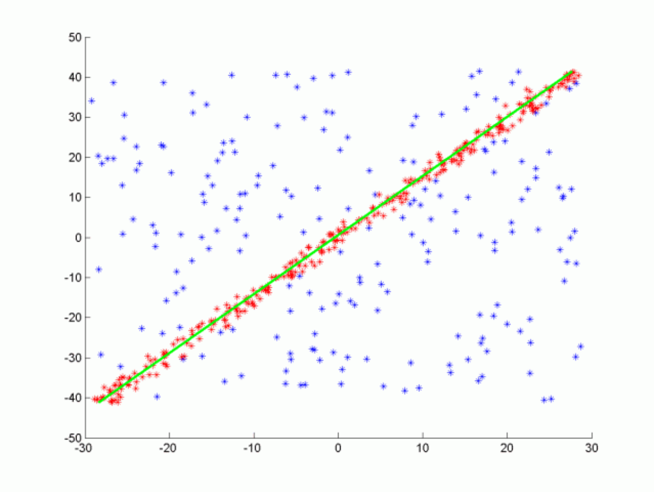
RANSAC



RANSAC



RANSAC



*SAC

several extensions exist in PCL:

- MSAC (weighted distances instead of hard thresholds)
- MLESAC (Maximum Likelihood Estimator)
- PROSAC (Progressive Sample Consensus)

also, several model types are provided in PCL:

- Plane models (with constraints such as orientation)
- Cone
- Cylinder
- Sphere
- Line
- Circle
- ...

Plane Fitting Example 1

So let's look at some code:

```
// necessary includes
#include <pcl/sample_consensus/ransac.h>
#include <pcl/sample_consensus/sac_model_plane.h>

// ...

// Create a shared plane model pointer directly
SampleConsensusModelPlane<PointXYZ>::Ptr model
  (new SampleConsensusModelPlane<PointXYZ> (input));

// Create the RANSAC object
RandomSampleConsensus<PointXYZ> sac (model, 0.03);

// perform the segmenation step
bool result = sac.computeModel ();
```

Here, we

- create a SAC model for detecting planes,
- create a RANSAC algorithm, parameterized on $\epsilon = 3cm$,
- and compute the best model (one complete RANSAC run, not just a single iteration!)

Example 1

```
// get inlier indices
boost::shared_ptr<vector<int> > inliers (new vector<int>);
sac.getInliers (*inliers);
cout << "Found␣model␣with␣" << inliers->size () << "␣inliers";

// get model coefficients
Eigen::VectorXf coeff;
sac.getModelCoefficients (coeff);
cout << ",␣plane␣normal␣is:␣" << coeff[0] << ",␣" << coeff[1] << ",␣"
```

We then

- retrieve the best set of inliers
- and the corr. plane model coefficients

Example 1

Optional:

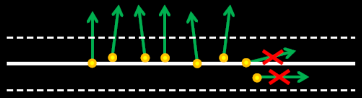
```
// perform a refitting step
Eigen::VectorXf coeff_refined;
model->optimizeModelCoefficients
  (*inliers, coeff, coeff_refined);
model->selectWithinDistance
  (coeff_refined, 0.03, *inliers);
cout << "After␣refitting,␣model␣contains␣"
                                << inliers->size () << "␣inliers";
cout << ",␣plane␣normal␣is:␣" << coeff_refined[0] << ",␣"
                                << coeff_refined[1] << ",␣"
                                << coeff_refined[2] << "." << endl;

// Projection
PointCloud<PointXYZ> proj_points;
model->projectPoints (*inliers, coeff_refined, proj_points);
```

If desired, models can be refined by:

- refitting a model to the inliers (in a least squares sense)
- or projecting the inliers onto the found model

Normal Estimation

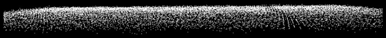
- Plane fitting can be supported by surface normals.



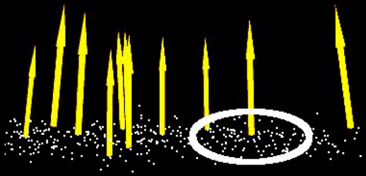
Normal Estimation

How do we compute normals in practice?

- Input: point cloud $\mathcal{P}$ of 3D points $p = (x, y, z)^T$



- Surface Normal Estimation:
  1. Select a set of points $\mathcal{Q} \subseteq \mathcal{P}$ from the neighborhood of p.
  2. Fit a local plane through $\mathcal{Q}$.
  3. Compute the normal $\vec{n}$ of the plane.



Available Methods

- Arbitrary Point Clouds:
  - we can not make any assumptions about structure of the point cloud
  - use FLANN-based KdTree to find approx. nearest neighbors (pcl::NormalEstimation)
- Organized Point Clouds:
  - regular grid of points (width $w \times$ height h)
  - but, not all points in the regular grid have to be valid
  - we can use:
    - FLANN-based KdTree to find approx. nearest neighbors (pcl::NormalEstimation)
    - or faster: an Integral Image based approach (pcl::IntegralImageNormalEstimation)

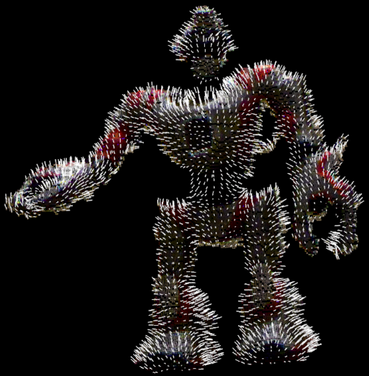
Normal Estimation

Normal Estimation using pcl::NormalEstimation

```
pcl::PointCloud<pcl::Normal>::Ptr normals_out
   (new pcl::PointCloud<pcl::Normal>);

pcl::NormalEstimation<pcl::PointXYZRGB, pcl::Normal> norm_est;

// Use a FLANN-based KdTree to perform neighborhood searches
norm_est.setSearchMethod
   (pcl::KdTreeFLANN<pcl::PointXYZRGB>::Ptr
     (new pcl::KdTreeFLANN<pcl::PointXYZRGB>));

// Specify the size of the local neighborhood to use when
// computing the surface normals
norm_est.setRadiusSearch (normal_radius);

// Set the input points
norm_est.setInputCloud (points);

// Set the search surface (i.e., the points that will be used
// when search for the input points' neighbors)
norm_est.setSearchSurface (points);

// Estimate the surface normals and
// store the result in "normals_out"
norm_est.compute (*normals_out);
```

Normal Estimation

Normal Estimation using pcl::NormalEstimation



Normal Estimation

Normal Estimation using pcl::IntegralImageNormalEstimation

```
  pcl::PointCloud<pcl::Normal>::Ptr normals_out
    (new pcl::PointCloud<pcl::Normal>);

  pcl::IntegralImageNormalEstimation<pcl::PointXYZRGB, pcl::Normal> no

  // Specify method for normal estimation
  norm_est.setNormalEstimationMethod (ne.AVERAGE_3D_GRADIENT);

  // Specify max depth change factor
  norm_est.setMaxDepthChangeFactor(0.02f);

  // Specify smoothing area size
  norm_est.setNormalSmoothingSize(10.0f);

  // Set the input points
  norm_est.setInputCloud (points);

  // Estimate the surface normals and
  // store the result in "normals_out"
  norm_est.compute (*normals_out);
}
```

Normal Estimation

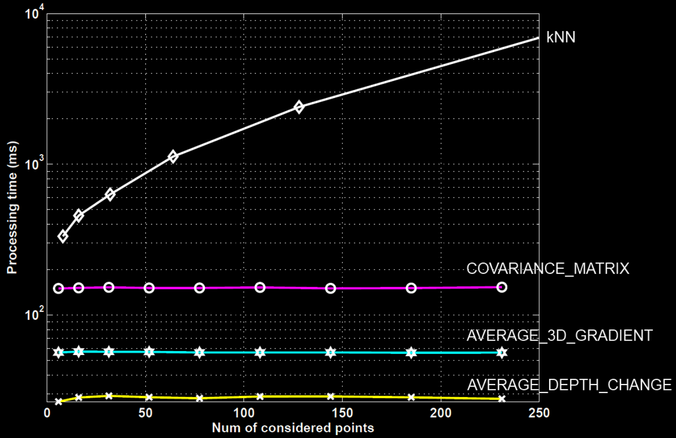
Normal Estimation using pcl::IntegralImageNormalEstimation

There are three ways of computing surface normals using integral images in PCL:

1. COVARIANCE_ MATRIX
   - Compute surface normal as eigenvector corresp. to smallest eigenvalue of covariance matrix
   - Needs 9 integral images
2. AVERAGE_3D_GRADIENT
   - Compute average horizontal and vertical 3D difference vectors between neighbors
   - Needs 6 integral images
3. AVERAGE_DEPTH_CHANGE
   - Compute horizontal and vertical 3D difference vectors from averaged neighbors
   - Needs 1 integral images

Normal Estimation

Comparison

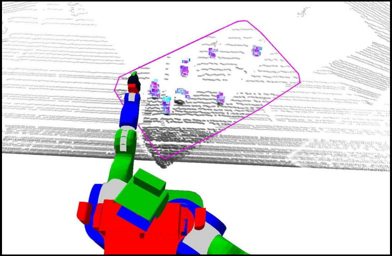


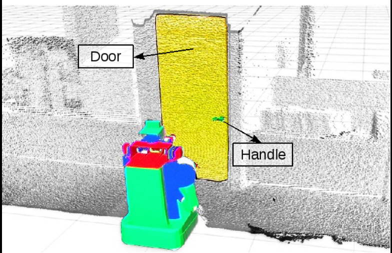
Plane Fitting Example 2

So let's look how we use the normals for plane fitting:

```
// necessary includes
#include <pcl/sample_consensus/ransac.h>
#include <pcl/sample_consensus/sac_model_normal_plane.h>

// ...

// Create a shared plane model pointer directly
SampleConsensusModelNormalPlane<PointXYZ, pcl::Normal>::Ptr model
  (new SampleConsensusModelNormalPlane<PointXYZ, pcl::Normal> (input));

// Set normals
model->setInputNormals(normals);
// Set the normal angular distance weight.
model->setNormalDistanceWeight(0.5f);

// Create the RANSAC object
RandomSampleConsensus<PointXYZ> sac (model, 0.03);

// perform the segmenation step
bool result = sac.computeModel ();
```

Polygonal Prism





Once we have a plane model, we can find

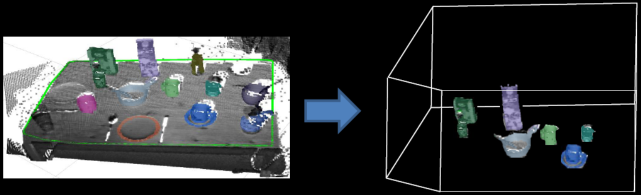
- objects standing on tables or shelves
- protruding objects such as door handles

by

- computing the convex hull of the planar points
- and extruding this outline along the plane normal

ExtractPolygonalPrismData

ExtractPolygonalPrismData is a class in PCL intended fur just this purpose.



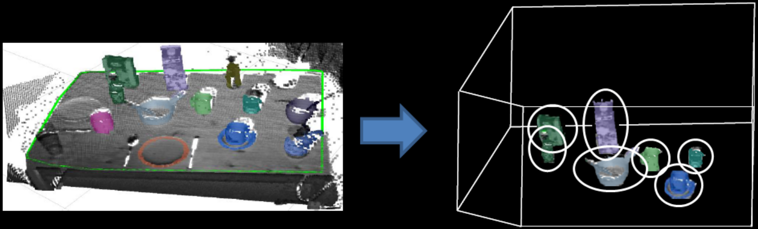
ExtractPolygonalPrismData

```
// Create a Convex Hull representation of the projected inliers
pcl::PointCloud<pcl::PointXYZ>::Ptr cloud_hull
  (new pcl::PointCloud<pcl::PointXYZ>);
pcl::ConvexHull<pcl::PointXYZ> chull;
chull.setInputCloud (inliers_cloud);
chull.reconstruct (*cloud_hull);

// segment those points that are in the polygonal prism
ExtractPolygonalPrismData<PointXYZ> ex;
ex.setInputCloud (outliers);
ex.setInputPlanarHull (cloud_hull);

PointIndices::Ptr output (new PointIndices);
ex.segment (*output);
```

Starting from the segmented plane,

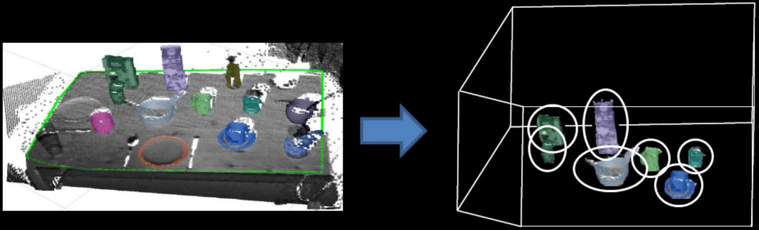
- we compute its convex hull,
- and pass it to a ExtractPolygonalPrismData object.

Table Object Detection



Finally, we want to segment the remaining point cloud into separate clusters. For a table plane, this gives us table top object segmentation.

Table Object Detection



The basic idea is to use a region growing approach that cannot "grow" / connect two points with a high distance, therefore merging locally dense areas and splitting separate clusters.

Clustering Example

```
// Create EuclideanClusterExtraction and set parameters
pcl::EuclideanClusterExtraction<PointT> ec;
ec.setClusterTolerance (cluster_tolerance);
ec.setMinClusterSize (min_cluster_size);
ec.setMaxClusterSize (max_cluster_size);

// set input cloud and let it run
ec.setInputCloud (input);
ec.extract (cluster_indices_out);
```

Very straightforward.

Compile & Try

- See RANSAC tutorial at:
  `http://www.pointclouds.org/documentation/tutorials/random_sample_consensus.php`
- See plane segmentation tutorial at:
  `http://www.pointclouds.org/documentation/tutorials/planar_segmentation.php`
- See normal estimation tutorialsl at:
  `http://www.pointclouds.org/documentation/tutorials/normal_estimation.php`
  `http://www.pointclouds.org/documentation/tutorials/normal_estimation_using_integral_images.php`

Compile & Try

- See projecting points using parametric model tutorial at: `http://www.pointclouds.org/documentation/tutorials/project_inliers.php`
- See convex/concave hull tutorial at: `http://www.pointclouds.org/documentation/tutorials/hull_2d.php`
- See euclidean clustering tutorial at: `http://www.pointclouds.org/documentation/tutorials/cluster_extraction.php`