PCL :: Segmentation

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Outline

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Session files

The C++ source files and data sets related to this session can be obtained from:

`http://ias.in.tum.de/people/blodow/rss_pcl_04.bz2`

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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

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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%

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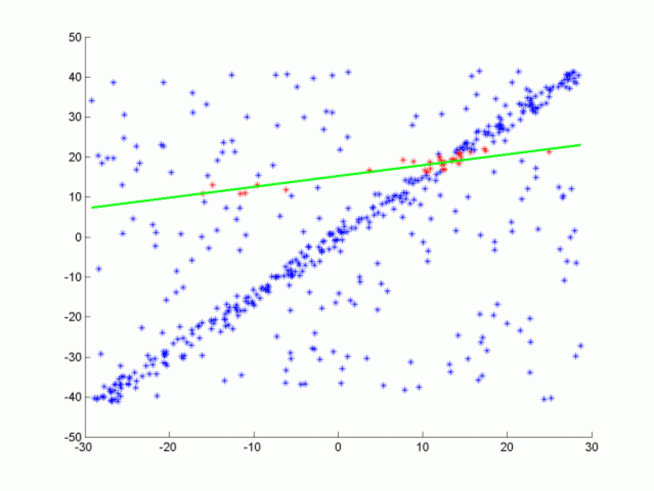
RANSAC



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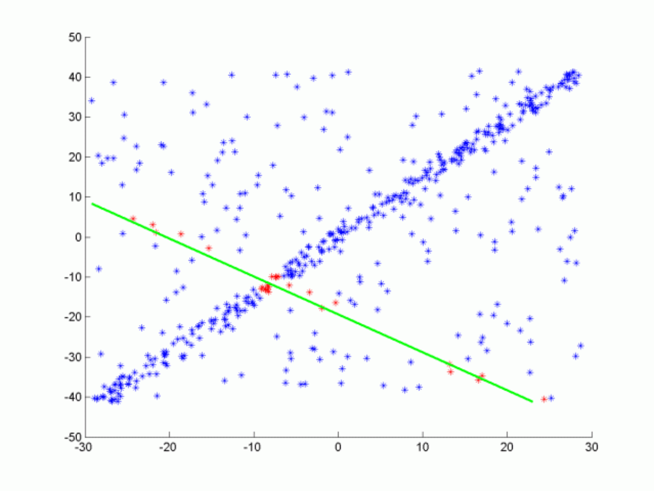

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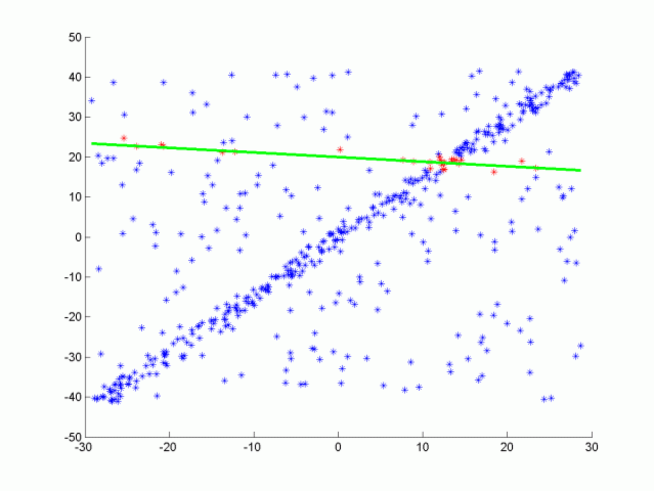

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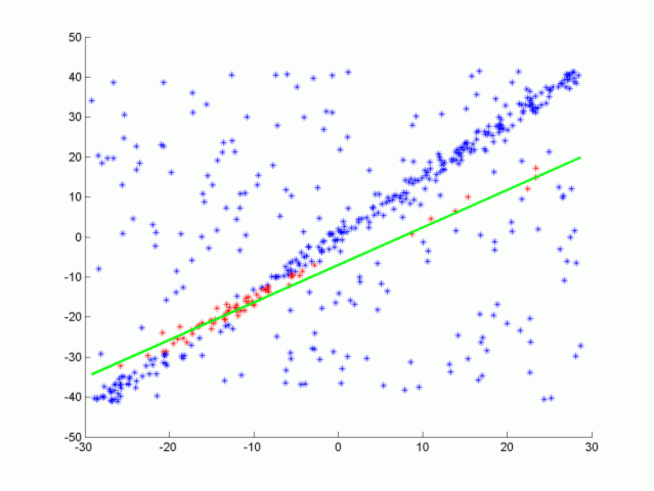
RANSAC



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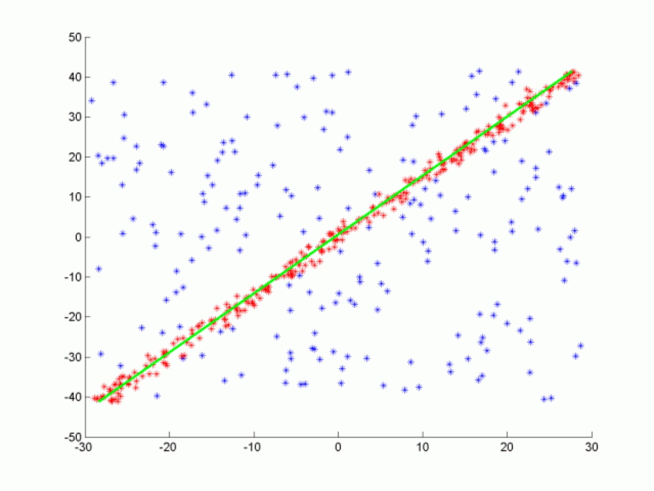
RANSAC



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*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
- ...

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Example 1

So let's look at some code: 04_sample_1.cpp

```
// some basic includes
#include <pcl/point_cloud.h>
#include <pcl/io/pcd_io.h>

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

// ...

// compute a planar model
void sample1 (const PointCloud<PointXYZ>::ConstPtr & input)
{
  // 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 ();

// ...
```

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Example 1

```
// 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!)

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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

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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

Sample 2

Sample 2 is just an “advanced” version of sample 1, including 3D visualization of the detected plane model:

```
// Create a visualizer
PCLVisualizer vis ("RSS␣2011␣PCL␣Tutorial␣-␣04␣Segmentation");

// Create the filtering object
ExtractIndices<PointXYZ> extract;

// Extract the inliers
extract.setInputCloud (input);
extract.setIndices (inliers);
extract.setNegative (false);
PointCloud<PointXYZ>::Ptr subcloud (new PointCloud<PointXYZ>);
extract.filter (*subcloud);

// finally, add both clouds to screen
vis.addPointCloud<PointXYZ>(input, WhiteCloudHandler (input), "cloud")
vis.addPointCloud<PointXYZ>
  (subcloud, RedCloudHandler (input), "inliers");
```

As you can see in the code, this whole segmentation process can become quite tedious, so PCL provides a more convenient wrapper in SACSegmentation.

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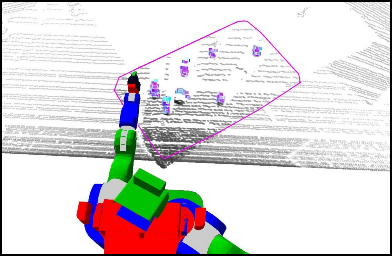
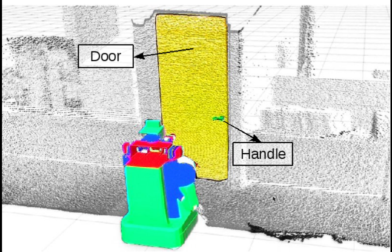
Polygonal Prism





Once we have a plane model, we can find

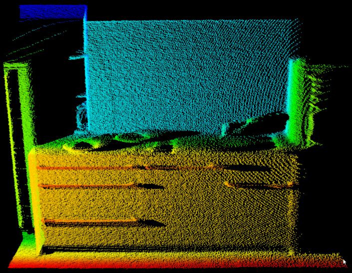
- objects standing on tables or shelves
- protruding objects such as door handles

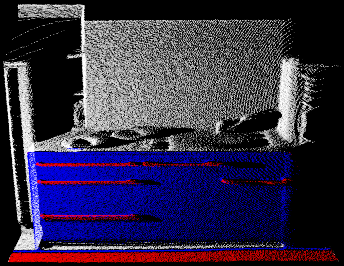
by

- 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.
In Sample 3, we will look at the front drawer handles of a kitchen:





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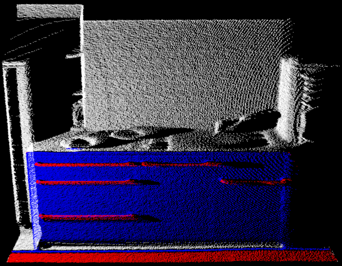
Sample 3

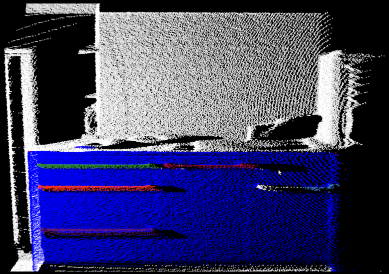
```
// Create a Convex Hull representation of the projected inliers
pcl::PointCloud<pcl::PointXYZ>::Ptr cloud_hull
  (new pcl::PointCloud<pcl::PointXYZ>);
pcl::ConvexHull<pcl::PointXYZ> chull;
chull.setInputCloud (inliers_cloud);
chull.reconstruct (*cloud_hull);

// 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 for the furniture fronts,

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

For our final example, we want to segment the point cloud containing all handles into separate handle clusters





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.

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Sample 4

```
// Creating the KdTree object for the search method of the extraction
KdTree<PointXYZ>::Ptr tree (new KdTreeFLANN<PointXYZ>);
tree->setInputCloud (subcloud);

vector<PointIndices> cluster_indices;
EuclideanClusterExtraction<PointXYZ> ec;
ec.setClusterTolerance (0.02); // 2cm
ec.setMinClusterSize (100);
ec.setMaxClusterSize (25000);
ec.setSearchMethod (tree);
ec.setInputCloud( subcloud);
ec.extract (cluster_indices);
```

We need

- to create a search structure for the points
- and a EuclideanClusterExtraction parameterized to the task.

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Outlook

When we combine these segmentation algorithms consequently, we can use them to effectively and efficiently process whole rooms:

`http://www.youtube.com/watch?v=U8zhJMsao34`