PCL :: Search

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Motivation

- Nearest neighbor search is an inner loop of many parts of PCL (filters, surface, features, registration)
  - Needs to be as fast as possible
- FLANN - Fast Library for Appproximate Nearest Neighbors
  - `http://www.cs.ubc.ca/~mariusm/flann`
  - C, C++, Matlab and Python bindings
  - Exact nearest neighbor search in low dimensional spaces (3D) using kd-trees
  - Approximate nearest neighbor search in high dimensional spaces
- Octree - 3D search

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Nearest Neighbor Search

- Nearest neighbor search problem
  - Given a set of points $P = p_1, p_2, ..., p_n$ in a metric space X, preprocess them in such a way that given a new point $q \in X$ finding the closest p_i to q can be done easily
- K-Nearest neighbor search
  - find the closest K neighbors
- Radius nearest neighbor search
  - find all the neighbors within a certain radius

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Outline

1. KdTree
2. 3D Nearest Neighbor Search
3. High Dimensional Nearest Neighbor Search
4. Octree

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The KD-Tree

- recursively divide the data points based on a single dimension
  - how to choose the dimension in which to divide the data?
  - where to divide?
- binary tree
- when searching entire branches can be ignored due to being too far away from the query point
- very efficient for low dimensionality data

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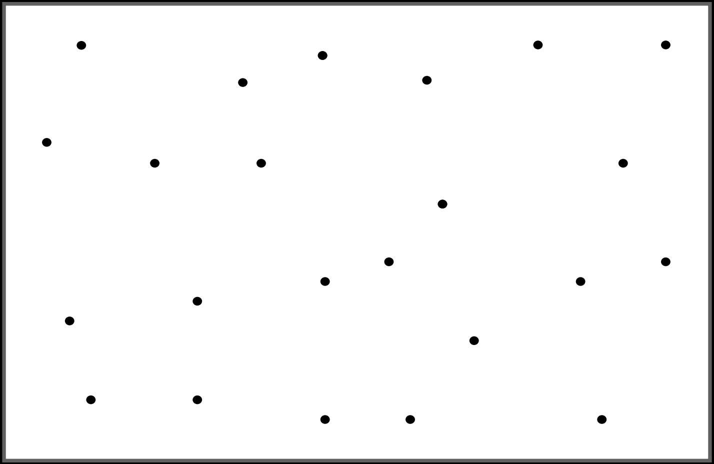
KD-Tree Example



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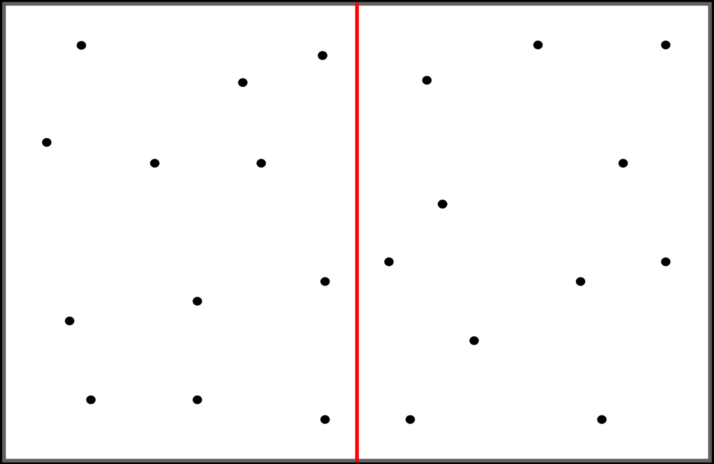
KD-Tree Example



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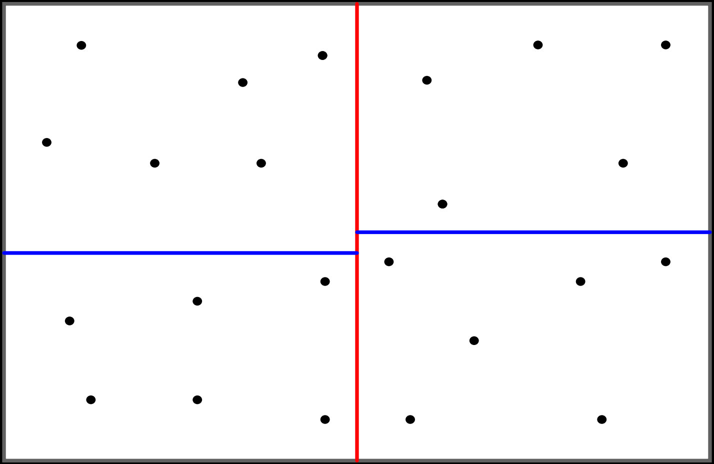
KD-Tree Example



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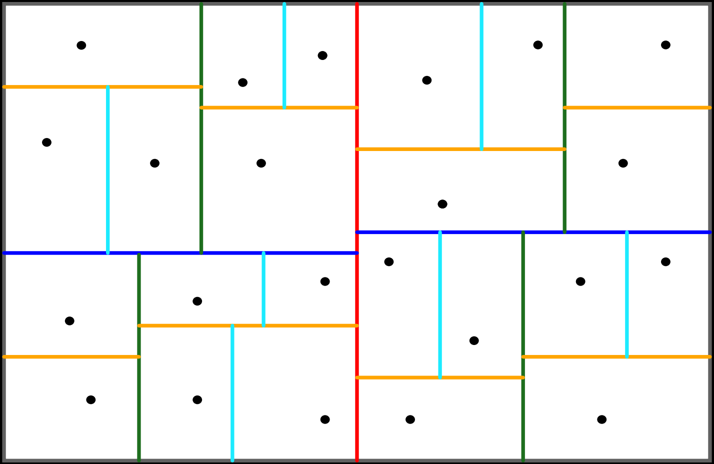
KD-Tree Example



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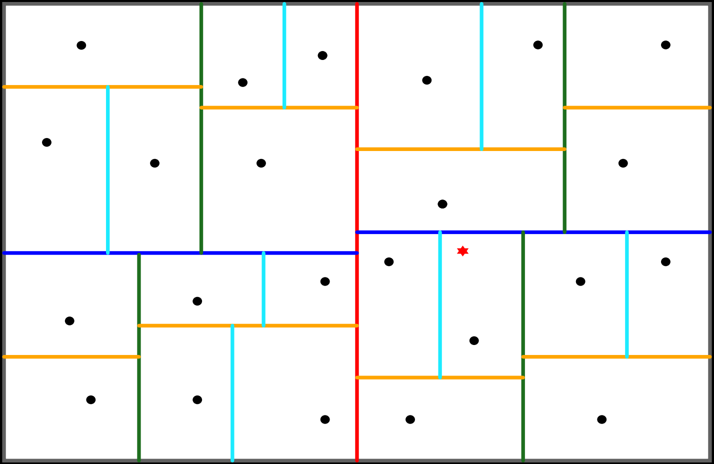
KD-Tree Example



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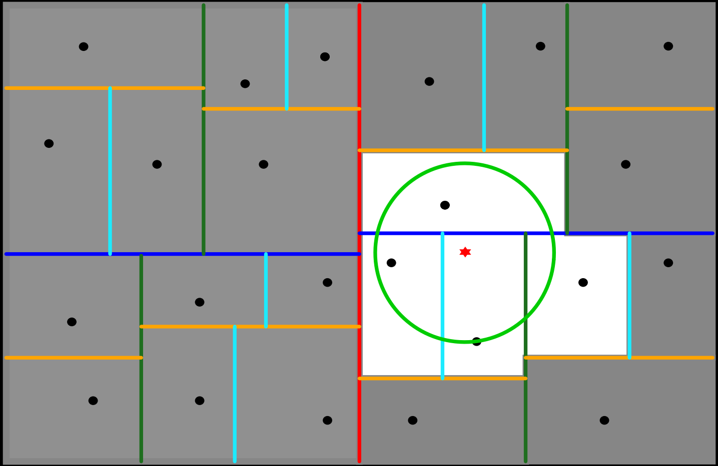
KD-Tree Example



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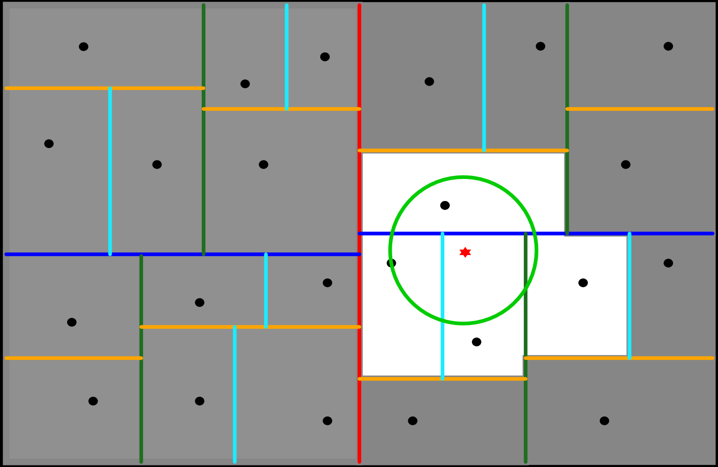
KD-Tree Example



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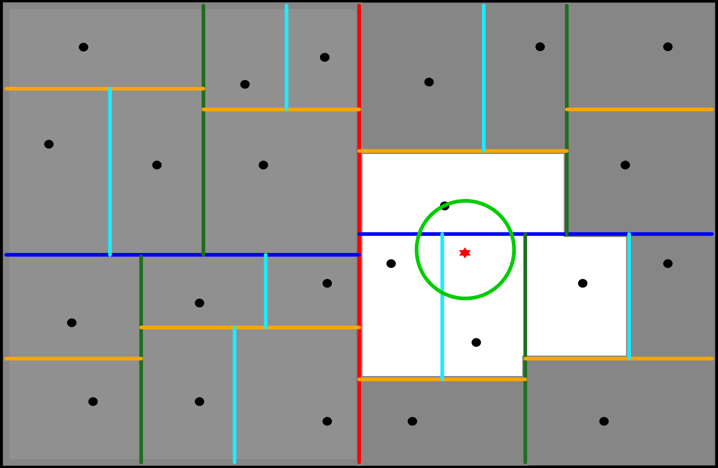
KD-Tree Example



GSOC

- during 2011 GSOC, 2 students are working on a GPU based kd-tree implemenattion
- encouraging preliminary results, speedups of 8-10x compared to CPU implementation

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FLANN in PCL

- Header: `#include <pcl/kdtree/kdtree_flann.h>`
- Class: `template<typename PointT> class pcl::KdTreeFLANN`
- K-nearest neighbor search

```
int nearestKSearch (const PointT &point, int k,
                    vector<int> &k_indices, vector<float> &k_distances);
```

- Radius search

```
int radiusSearch (const PointT &point, double radius,
                  vector<int> &k_indices,
                  vector<float> &k_distances, int max_nn = -1);
```

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KNN Search Example

```
PointCloud<PointXYZ>::Ptr cloud (new PointCloud<PointXYZ>);
PointXYZ searchPoint;

// ... populate the cloud and the search point

// create a kd-tree instance
KdTreeFLANN<PointXYZ> kdtree;

// assign a point cloud - this builds the tree
kdtree.setInputCloud (cloud);

// pre-allocate the neighbor index and
// distance vectors
int K = 10;
std::vector<int> pointsIdx(K);
std::vector<float> pointsSquaredDist(K);

// K nearest neighbor search
kdtree.nearestKSearch (searchPoint, K, pointsIdx, pointsSquaredDist);
```

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Radius Search Example

```
PointCloud<PointXYZ>::Ptr cloud (new PointCloud<PointXYZ>);
PointXYZ searchPoint;

// ... populate the cloud and the search point

// create a kd-tree instance
KdTreeFLANN<PointXYZ> kdtree;

// assign a point cloud - this builds the tree
kdtree.setInputCloud (cloud);

std::vector<int> pointIdxRadius;
std::vector<float> pointsSquaredDistRadius;
float radius = ...;

// radius search
int count = kdtree.radiusSearch (searchPoint, radius,
                pointIdxRadiusSearch, pointsSquaredDistRadius);
```

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Compile & Try

```
$ cd $PCL_ROOT/doc/tutorials/content/sources/kdtree_search
$ mkdir build
$ cd build
$ cmake ..
$ make
$ ./kdtree_search
K nearest neighbor search at (701.248 662.202 554.841) with K=10
   702.91 601.583 521.043 (squared distance: 4819.7)
   676.792 699.92 482.203 (squared distance: 7297.07)
   731.215 717.665 491.714 (squared distance: 7959.15)
   670.142 707.355 476.051 (squared distance: 9214.31)
   681.636 728.872 479.31 (squared distance: 10534.5)
   683.843 581.742 492.494 (squared distance: 10663.9)
   696.085 705.888 457.71 (squared distance: 11369.7)
   683.603 667.109 430.477 (squared distance: 15801.9)
   721.228 684.503 430.334 (squared distance: 16398.5)
   829.566 676.396 560.64 (squared distance: 16700.6)
Neighbors within radius search at (701.248 662.202 554.841) with
radius=114.069
   702.91 601.583 521.043 (squared distance: 4819.7)
   676.792 699.92 482.203 (squared distance: 7297.07)
   731.215 717.665 491.714 (squared distance: 7959.15)
   670.142 707.355 476.051 (squared distance: 9214.31)
   681.636 728.872 479.31 (squared distance: 10534.5)
   683.843 581.742 492.494 (squared distance: 10663.9)
   696.085 705.888 457.71 (squared distance: 11369.7)
```

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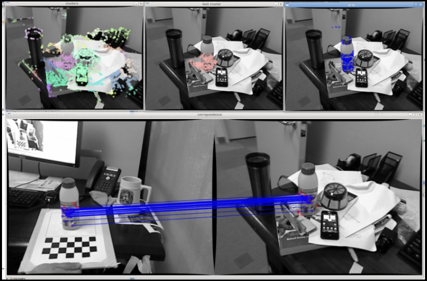
Motivation

- Object recognition (TOD)



TOD ©Willow Garage

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Motivation

- Object recognition (TOD)
- Image stitching (AutoStitch, Hugin)

AutoStitch ©Matthew Brown

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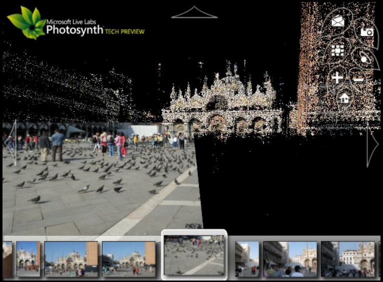
Motivation

- Object recognition (TOD)
- Image stitching (AutoStitch, Hugin)
- 3D Reconstruction (Photosynth)



Photosynth ©Microsoft Corporation

Motivation

- Object recognition (TOD)
- Image stitching (AutoStitch, Hugin)
- 3D Reconstruction (Photosynth)
- 3D object classification (VFH)

VFH Classification example

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Motivation

- Object recognition (TOD)
- Image stitching (AutoStitch, Hugin)
- 3D Reconstruction (Photosynth)
- 3D object classification (VFH)
- Content based image retrieval

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Motivation

- Object recognition (TOD)
- Image stitching (AutoStitch, Hugin)
- 3D Reconstruction (Photosynth)
- 3D object classification (VFH)
- Content based image retrieval
- Visual SLAM

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High Dimensional Search

- For high dimensionality data, no exact algorithm faster than linear search is known
- Approximate nearest neighbor search is used to obtain large speedups
- FLANN contains several algorithms for high dimensional approximate nearest neighbor search
  - KDTreeIndex (randomized kd-tree forest)
  - KMeansIndex (hierarchical k-means tree)
  - HierarchicalClusteringIndex (clustering tree in a generic metric space)*
  - LshIndex (locality sensitive hashing)*

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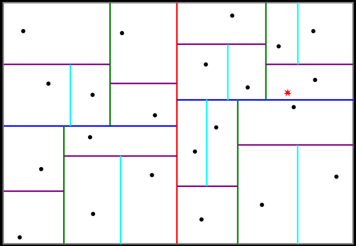
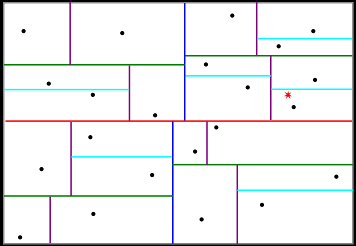
Randomized KD-Trees

- multiple trees are build in parallel
- the split dimension is chosen randomly from the first D dimensions with greatest variance (D=5)
- at search time a single priority queue is used across all trees
- search is terminated after a predefined number of tree leafs are checked





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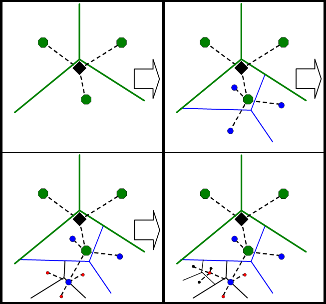
Hierarchical K-Means Tree

- Building the tree
  - built by splitting the data at each level of the tree using k-means clustering
  - apply the same procedure recursively on each cluster
  - just a few iterations of the k-means clustering give good results
- Exploring the tree
  - unexplored branches are added to a priority queue while traversing the tree
  - restart search from best branch in the priority queue



(Nistér & Stewénius, 2006)

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FLANN Usage

- Header: `#include <flann/flann.h>`
- Class: `template<typename Distance> class flann::Index`
- K-nearest neighbor search

```
void knnSearch(const Matrix<ElementType>& queries,
            Matrix<int>& indices, Matrix<DistanceType>& dists,
            int knn, const SearchParams& params)
```

- Radius search

```
int radiusSearch(const Matrix<ElementType>& query,
            Matrix<int>& indices, Matrix<DistanceType>& dists,
            float radius, const SearchParams& params)
```

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FLANN Search Example

```
flann::Matrix<float> data;
flann::Matrix<float> queries;
// populate the matrix with features
// one feature/row

// build randomized kd-tree index (4 trees)
flann::Index< L2<float> > index(data, flann::KDTreeIndexParams(4));
index.buildIndex();

// allocate memory for results
int k = 10;
int n = queries.rows;
flann::Matrix<int> k_indices(new int[n*k], n, k);
flann::Matrix<float> k_distances(new float[n*k], n, k);

// KNN search
index.knnSearch (queries, k_indices, k_distances, k,
                 flann::SearchParams(256));
```

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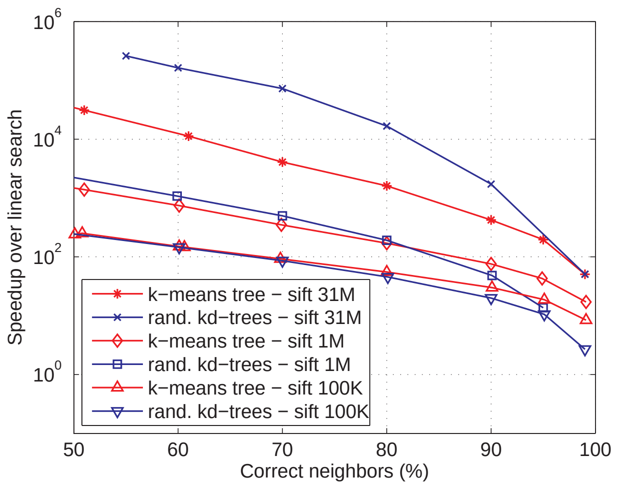
Search Precision

- Speedup with precision for different dataset sizes



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VFH Recognition

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VFH Recognition

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Compile & Try

- See tutorial at: http://www.pointclouds.org/documentation/tutorials/vfh_recognition.php

```
$ cd $PCL_ROOT/doc/tutorials/content/sources/vfh_recognition
$ wget http://dev.pointclouds.org/attachments/download/216/
vfh_recognition_tutorial_data.tbz
$ tar -xzf vfh_recognition_tutorial_data.tbz
$ mkdir build
$ cd build
$ cmake ..
$ make
$ cd ..
$ ./build/build_tree data
...
$ ./build/nearest_neighbors -k 16 -thresh 50 data/000.580.67/
1258730231333_cluster_0_nxyz_vfh.pcd
```

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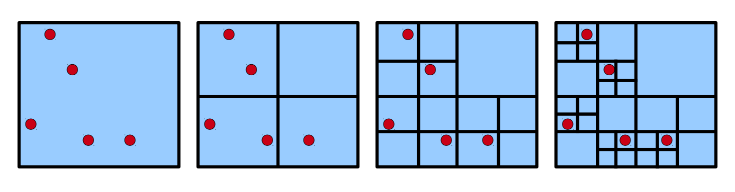
Octree Overview

Octree - 3D hierachical spatial tree data structure

- Recursive divide & conquer algorithm
- Binary subdivision of occupied cells into 8 octants (voxels)

2D Example (Quadtree):



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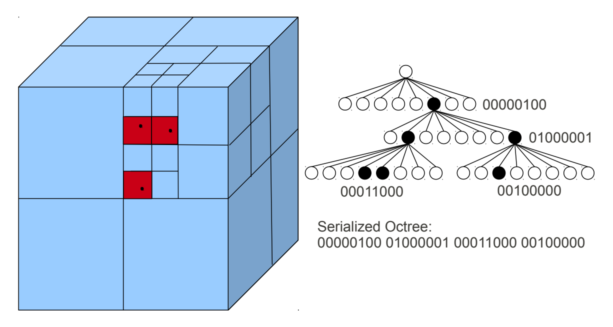
Octree Overview



- Root node describes a cubic bounding box which encapsulates all points
- Child nodes recursively subdivide point space
- Nodes have up to eight children $\Rightarrow$ Byte encoding

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Octree Usage

Instantiate octree:

```
float voxelSize = 0.01f; // voxel resolution
OctreePointCloud<PointXYZ>  octree (voxelSize);
```

Set input point cloud (via Boost shared pointers):

```
octree.setInputCloud (cloud);
```

Define octree bounding box (optional):

```
// calculate bounding box of input cloud
octree.defineBoundingBox ();
// manually define bounding box
octree.defineBoundingBox (minX, minY, minZ, maxX, maxY, maxZ);
```

Add points from input cloud to octree:

```
octree.addPointsFromInputCloud ();
```

Delete octree data structure:
(pushes allocated nodes to memory pool!)

```
octree.deleteTree ();
```

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Data/Voxel Access

Check if voxel at given point coordinates exist:

```
double X,Y,Z;
bool occuppied;
X = 1.0; Y=2.0; Z=3.0;
occuppied = octree.isVoxelOccupiedAtPoint (X, Y, Z);
```

Get center points of all occupied voxels:
(voxel grid filter/downsampling)

```
std::vector<PointXYZ> pointGrid;
octree.getOccupiedVoxelCenters (pointGrid);
```

Delete voxel:

```
pcl::PointXYZ point_arg( 1.0, 2.0, 3.0 );
octree.deleteVoxelAtPoint ( point );
```

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Octree Applications

Provided algorithms in PCL using octrees for spatial decomposition:

- Search operations (neighbor search, radius search, voxel search)
- Downsampling (Voxel-grid / Voxel-centroid filter)
- Point cloud compression
- Spatial change detection
- Spatial point density analysis
- Occupancy checks/maps
- Collision detection
- ...

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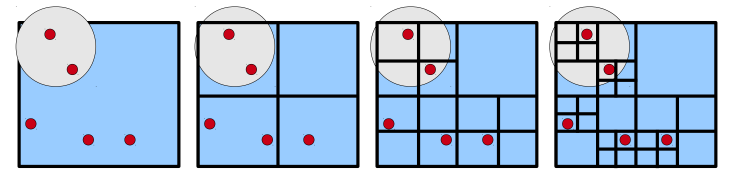
Neighbor Search I

Points within radius search

- Depth first tree exploration
- At every node investigate occupied child voxels that overlap with search sphere



K nearest neighbor search:

- Priority queue (binary heap) of nodes and point candidates
- Investigate occupied child voxels (closest voxel first)
- Radius search with radius=distance to Kth point candidate
- Update radius with every new point candidate

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Neighbor Search II

Define search precision / error bound:

```
octree.setEpsilon (double eps); // default: 0.0
```

Neighbors within voxel search:

```
std::vector<int> pointIdxVec;

if (octree.voxelSearch (searchPoint, pointIdxVec))
{
  for (size_t i = 0; i < pointIdxVec.size (); ++i)
    std::cerr << " " << cloud->points[pointIdxVec[i]].x
      << " " << cloud->points[pointIdxVec[i]].y
      << " " << cloud->points[pointIdxVec[i]].z << std::endl;
}
```

K nearest neighbor search:

```
int K = 10;
std::vector<int> pointIdxNKNSearch;
std::vector<float> pointNKNSquaredDistance;

if ( octree.nearestKSearch (searchPoint, K,
       pointIdxNKNSearch, pointNKNSquaredDistance) > 0 )
{
  ...
}
```

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Neighbor search III

Neighbors within radius search:

```
std::vector<int> pointIdxRadiusSearch;
std::vector<float> pointRadiusSquaredDistance;
float radius = 0.1;

if ( octree.radiusSearch (searchPoint, radius,
      pointIdxRadiusSearch, pointRadiusSquaredDistance) > 0 )
{
  ...
}
```

Approx. neighbors within radius search:
(only scans points within “search point voxel”)

```
std::vector<int> pointIdxRadiusSearch;
std::vector<float> pointRadiusSquaredDistance;
float radius = 0.1;

if ( octree.approxNearestSearch (searchPoint, radius,
     pointIdxRadiusSearch, pointRadiusSquaredDistance) > 0 )
{
  ...
}
```

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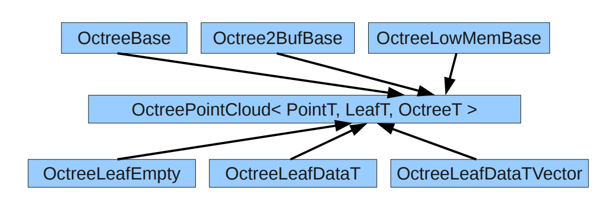
Octree Implementation

Template configuration:



Optimized performance&memory usage:

- Select octree base implementation
- Select/define leaf node class
- Serialization callbacks (serializeLeafCallback, deserializeLeafCallback, serializeNewLeafCallback)

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Octree instantiation

OctreePointCloud classes:

```
float resolution = 0.01f;

// equal to OctreePointCloudPointVector<PointXYZ>
OctreePointCloud<PointXYZ>  octreeA (resolution);

// manages indices vectors in leaf nodes
OctreePointCloudPointVector<PointXYZ> octreeB (resolution);
// keeps a single point indices in leaf nodes
OctreePointCloudSinglePoint<PointXYZ> octreeC (resolution);
// does not store any point information in leaf node
OctreePointCloudOccupancy<PointXYZ> octreeD (resolution);
```

Octree-Base selection via typedefs:

```
OctreePointCloud<PointXYZ>::SingleBuffer octreeSB (resolution);
OctreePointCloud<PointXYZ>::DoubleBuffer octreeDB (resolution);
OctreePointCloud<PointXYZ>::LowMem octreeLM (resolution);
```

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Double Buffering

Octree2BufBase implementation:

- Create octrees at high rate
- Advanced memory management:
  - Previous tree structure is kept in memory
  - Maximum reusage of already allocate branch&leaf nodes
  - Unused node instances are pushed to a memory pool for later reusage
- Enables comparison of octree structure (change detection)

Switching between octree buffers:

```
octree.switchBuffers ();
```

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Change Detection

```
class SimpleSpatialChangeDetection
{
public:
  OctreePointCloudChangeDetector<PointXYZRGB>* octree;
  ...
  void
  cloud_cb_ (const pcl::PointCloud<pcl::PointXYZRGB>::ConstPtr &cloud)
  {
    if (!viewer.wasStopped ())
    {
      // Switch octree buffers
      octree.switchBuffers ();

      // Add points from cloud to octree
      octree.setInputCloud (cloud);
      octree.addPointsFromInputCloud ();

      std::vector<int> newPointIdxVector;

      /* Get vector of point indices from octree voxels
         which did not exist in previous buffer */
      octree.getPointIndicesFromNewVoxels (newPointIdxVector);
      ...
    }
  }
};
```

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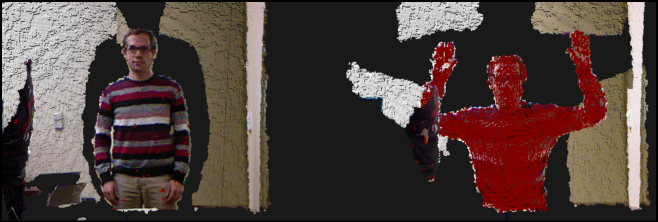
Change Detection



- Real-time spatial change detection
  based on XOR comparison of octree structure

DEMO: See /visualization/tool/openni_change_viewer

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Extending the Octree

Example: Point density estimation
Design your own leaf node class:

```
template<typename DataT>
class OctreePointCloudDensityLeaf : public OctreeLeafAbstract<DataT>
{
public:
  ...

  virtual void
  setData (const DataT& point_arg)
  {
   pointCounter_++;
  }

  unsigned int
  getPointCounter ()
  {
   return pointCounter_;
  }

  ...

private:
  unsigned int pointCounter_;
};
```

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Extending the Octree

.. and your own OctreePointCloud class:

```
class OctreePointCloudDensity : public OctreePointCloud
   <PointT, OctreePointCloudDensityLeaf<int> , OctreeT>
{
public:
  ...

  unsigned int
  getVoxelDensityAtPoint (const PointT& point_arg) const
  {
    unsigned int pointCount = 0;

    OctreePointCloudDensityLeaf<int>* leaf =
       this->findLeafAtPoint (point_arg);

    if (leaf) pointCount = leaf->getPointCounter ();

    return pointCount;
  }
};
```

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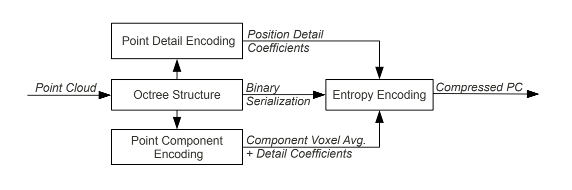
Point Cloud Compression

Encoding Pipeline:



Example:

```
/* for a full list of profiles see:
     /io/include/pcl/compression/compression_profiles.h */
compression_Profiles_e compressionProfile =
  pcl::octree::MED_RES_ONLINE_COMPRESSION_WITH_COLOR;

// instantiate point cloud compression for encoding and decoding
PointCloudCompression<PointXYZ> PointCloudEncoder (compressionProfile)
PointCloudCompression<PointXYZ> PointCloudDecoder ();
...
// iostream to read/write compressed point cloud data
std::stringstream compressedData;

// compress & decompress point cloud
PointCloudEncoder->encodePointCloud (cloud, compressedData);
PointCloudDecoder->decodePointCloud (compressedData, cloudOut);
```

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Compile & Try

- See octree search tutorial at:
  `http://pointclouds.org/documentation/tutorials/octree.php`
- See point cloud compression tutorial at:
  `http://pointclouds.org/documentation/tutorials/compression.php`
- See change detection tutorial at:
  `http://pointclouds.org/documentation/tutorials/octree_change.php`

- Point cloud compression and streaming app:
  `PCL_ROOT/apps/openni_stream_compression`
- Change detection app:
  `PCL_ROOT/visualization/tools/openni_change_viewer`