Development of a Robust Indoor 3D SLAM Algorithm

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Introduction

- Problem:
  - Create Map during Exploration of Environment
  - Must Know Location to Accurately Create Map
  - Must have a map to accurately find location.
- Applications
  - Search and Rescue
  - Home Health
- Simultaneous Localization and Mapping (SLAM)
  - Appearance Based SLAM
  - Depth Based SLAM
- Turtlebot 2.0
  - Sensors:
    - Microsoft Kinect
    - Inertial Unit
    - Bump and Cliff Sensors
  - Laptop: Asus X200-CA
    - Celeron 100070U @ 1.3 GHz
    - 4 GB RAM
    - 320 GB Hard Drive


from www.turtlebot.com

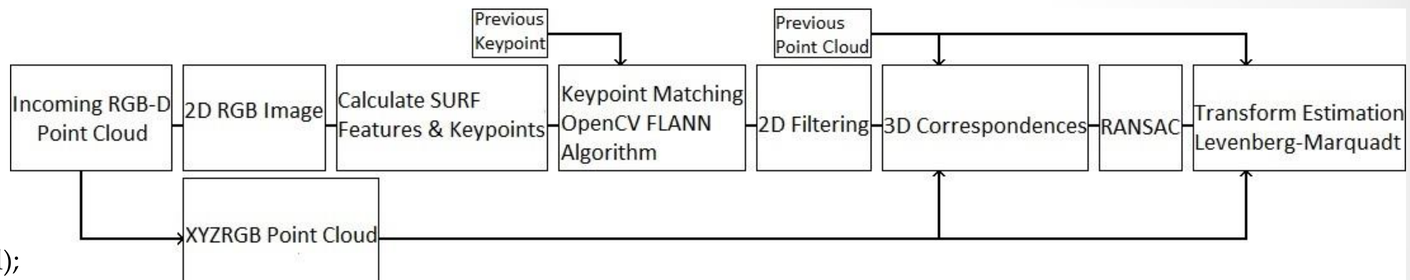
3D SLAM Algorithms

- 3D SLAM
  - Appearance Based SLAM
    - Use Color Features
  - Depth Based SLAM
    - Uses Depth Features

- Our Algorithm
  - Calculates Color Features
  - Combine Color Features with Depth Information
  - Find Matching Keypoints of Color and Depth Features
  - Calculate Transformation based on Keypoints.

Outline of Algorithm

- Input: Sequential RGB-D Point Clouds
- Output: 3D Point Cloud Aligned into single frame




```
3D_SLAM{
  Clouds = {};
  Keypoints = {};
  Descriptors = {};
  Transform = I
  while(!user.quit()){
    cloud = get_next_cloud();
    Clouds.append(cloud);
    img = get_2d_image(cloud);
    feature, keypoint = get_2D_keypoints(img);
    Keypoints.append(keypoint);
    Descriptors.append(feature);
    if (length(Clouds) > 1){
      2D_corr = get_2D_correspondences(Keypoints[-1], Descriptors[-1],Keypoints[-2], Descriptors[2]);
      3D_corr = get_3D_correspondences(2D_corr, Clouds[-1], Clouds[-2]);
      RANSAC(3D_corr);
      Transform = get_transform(3D_corr);
      Clouds[-1] *= Transform;
    }
  }
}
```

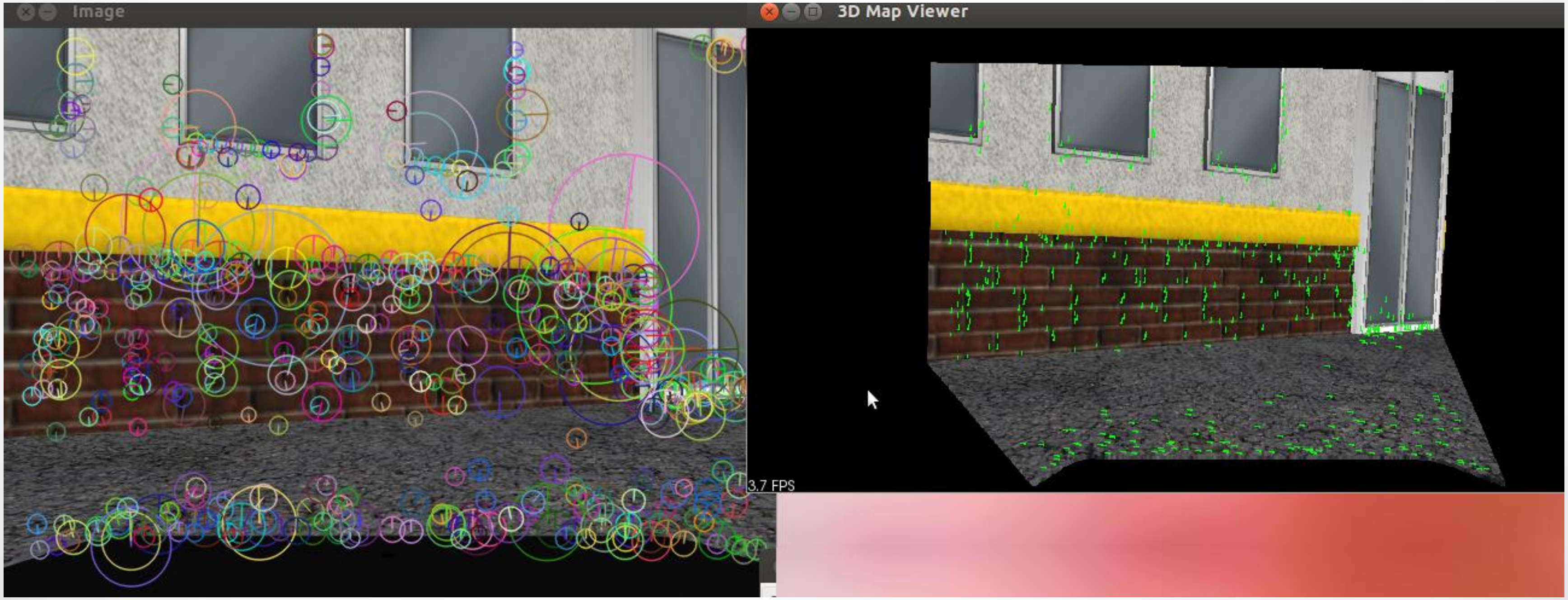
Feature Extraction

- Features
  - Image Structures: Points, Edges, Corners, Objects
  - Local properties of an image
  - Invariant to Translation, Scale, Rotation
- Importance
  - Improve Performance
  - Allows comparison of Images
  - Should be invariant to Transforms

Surf Features (from www.opencv.com)

SURF Features

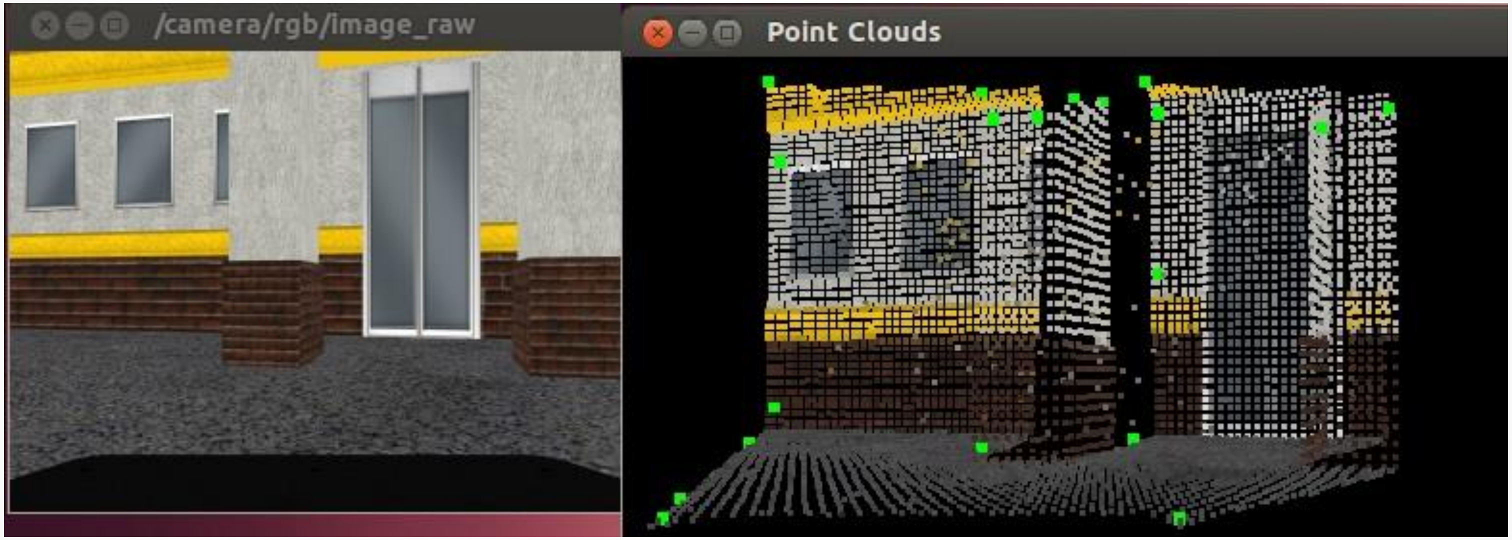
- Speeded Up Robust Features (SURF) – OpenCV
  - Local Feature Detector and Keypoint Finder
  - Uses Hessian Blob Detector
    - Affine-invariant feature detector based on second partial derivatives of image smoothed using a Gaussian Kernel



Surf Keypoints 2D image (left) SURF Keypoints shown in 3D Coordinate Space (right).

NARF Features

- Normal Aligned Radial Features (NARF) – PCL
  - Local Feature Detector and Keypoint Finder
  - Calculates change of normal around points of interest using depth image.



2D Image (left) Down Sampled Point Cloud & extracted NARF Features (right)

- SURF vs NARF
  - SURF Feature Extraction takes 0.133 Seconds
  - NARF Feature Extraction takes 14.405 Seconds
  - SURF Features produces more Keypoints that were more stable.

Keypoint Correspondences

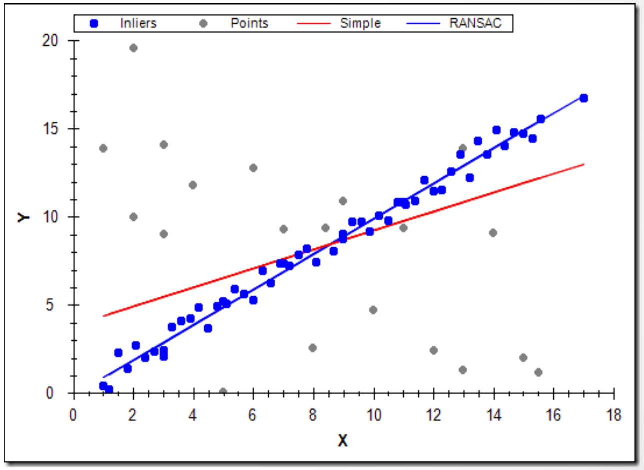
- Calculate Corresponding Keypoints
  - OpenCV's Fast Library for Approximating Nearest Neighbors (FLANN)
- Filter Results using Threshold
  - All transforms between images are Affine (Scale, Translation, Rotation)
  - Distance between corresponding keypoints should be similar
  - Reject any Correspondences that are too far apart
- Remaining Keypoints are Associated into 3D Space
  - Reverse Process of calculating 2D Image from 3D point Cloud

SURF Keypoint Correspondences

SURF Keypoint Matches in 2D Image. Incoming Image (left) Previous Image(right)

RANSAC

- Random Sample Consensus (RANSAC)
  - Iterative Method for estimating parameters of a Mathematical Model
    - Select random sample of data points to fit model
    - Test remaining points if they fit the model.
  - Produces a set of Inliers and Outliers
    - Inliers are the data points that fit the model
    - Outliers are the points that do not
  - Try to maximize the set of Inliers



from http://crsouza.blogspot.com/

- Use RANSAC on 3D Correspondences
  - Reject the outlier set
  - Remove poorly matched Correspondences

Transformation Estimation

- Levenberg Marquardt Transformation Estimation
  - Non-linear minimization of least-square cost function
    - Distance between corresponding keypoints
  - Iterative method for finding Rigid Transform Estimation

- Singular Value Decomposition
  - Used to minimize least squares of cost function
  - Can have closed form solution to find Rigid Transformation Matrix

Further Improvements

- Additional Keypoint types
  - BRISK, SIFT, FAST keypoints
  - Use Multiple Keypoint types
  - Determine which keypoint type works best in current environment
- Improve Levenberg Marquardt method
  - Alter implementation to allow to test for convergence of point clouds
  - Calculate how well aligned the resulting transformation is
- Loop Closure
  - Allows the robot to know it has already seen the area before
  - Adds additional constraints to the map to improve errors in map
- Increase robustness, reliability and the quality of the generated Map for future navigation purposes.

Conclusion

- Current results produce a 3D Map that combines all input Point Clouds.

- These Results can be improved for better performance and accuracy of the Map.

Questions

References

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- [11] Description of Microsoft Kinect and how it can be used can be found at http://www.microsoft.com/en-us/kinectforwindows/meetkinect/features.aspx
- [12] For specifics on OpenCV, PCL, and ROS visit http://www.opencv.org, http://pointclouds.org, and http://www.ros.org respectively.
- [13] http://crsouza.blogspot.com/2010/06/random-sample-consensus-ransac-in-c.html