

Fast Point Feature Histograms (FPFH) for 3D Registration

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Project 6



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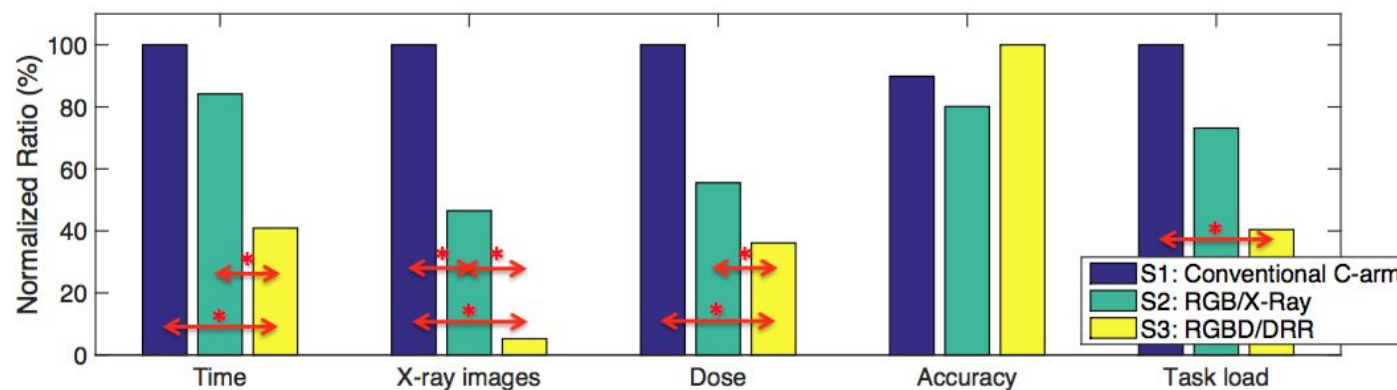
Review

Project Background and Objective

Orthopaedic surgeries are time intensive and require multiple images to ensure correct placement and direction of tools

Research has been done to create a manual calibration algorithm, that creates an intra-operative mixed-reality visualization

Goal is to automate the calibration process between CBCT scanner and RGBD camera



Paper Selection - from PCL Library

Rusu RB, Blodow N, Beetz M. 2009. Fast point feature histograms (FPFH) for 3D registration. In Proceedings of the 2009 IEEE international conference on Robotics and Automation (ICRA'09). IEEE Press, Piscataway, NJ, USA, 1848-1853.



Post FPFH
Calibration

RGBD and CBCT calibration fails
to converge to global minimum

Look for a different registration
approach (feature based)

Manual calibration algorithm
developed for this project uses
this algorithm

Improve usage of this algorithm,
or find a comparable algorithm for
an initial registration



Problem

3D point cloud to point cloud registration algorithms are used to align two different views of an object in space

This alignment is performed by finding the best transformation (rotation and translation)

Many typical optimization techniques can be utilized to find the transformation that minimizes the distance between respective points in the two clouds

Often times these algorithms fail because they become trapped in a local minimum and converge even though a better solution exists



Key Result and Significance

This paper proposes a new algorithm using fast point feature histograms (FPFH) to perform an initial alignment that places a registration into the correct global minimum space

The algorithm builds upon previous work of the author that proposed a novel way to analyze geometric features of a point cloud, called point feature histograms (PFH)

FPFH computations are faster compared than PFH computations ($O(k)$ vs. $O(k^2)$) to build per point

Provide implementation results for 3D point-cloud to point-cloud registration, using a sample consensus initial alignment algorithm (SAC-IA)



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Point Feature Histograms (PFH)

Point Feature Histograms (PFH) are previously proposed pose-invariant local features

Point, p in a cloud and the surface normal, n , at that point, as well as relevant information from p 's nearest neighbors

Radius r is chosen, and all neighbors to a point p with distance $\leq r$ are selected. Suppose uniform density, and thus about k neighbors per point

For each pair of points $p_i, p_j, i \neq j$ in this neighborhood with normals n_i, n_j , the following **frame** (u, v, n) is calculated as follows:

$$u = n_i$$

$$v = (p_j - p_i) \times u$$

$$w = u \times v$$



Point Feature Histograms (PFH)

From these the following **angular variations** of the surface normals are found:

$$u = n_i$$

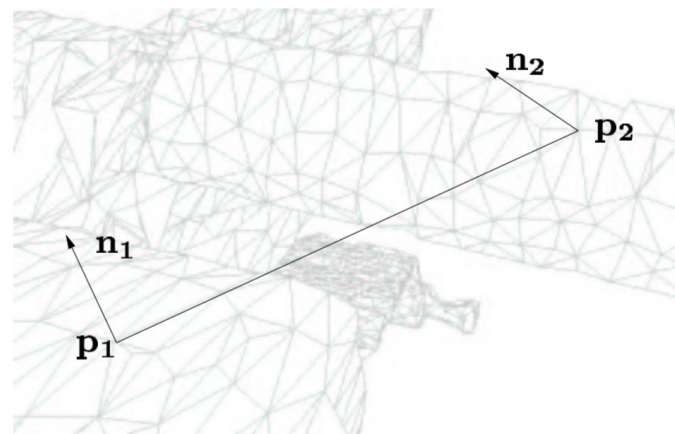
$$v = (p_j - p_i) \times u$$

$$w = u \times v$$

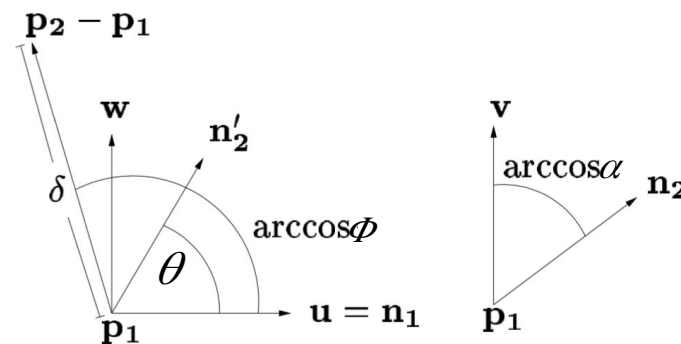
$$\alpha = v \cdot n_j$$

$$\phi = \frac{(u \cdot (p_j - p_i))}{\|p_j - p_i\|}$$

$$\theta = \arctan(w \cdot n_j, u \cdot n_j)$$



(a)



(Wahl et al.)



Persistence

$O(k^2)$ pieces of information per point p

Disregard points with similar PFHs

Finding the mean PFH of a dataset, μ and only selecting less common points outside of some range $\mu \pm \beta\sigma$ for some user-defined β

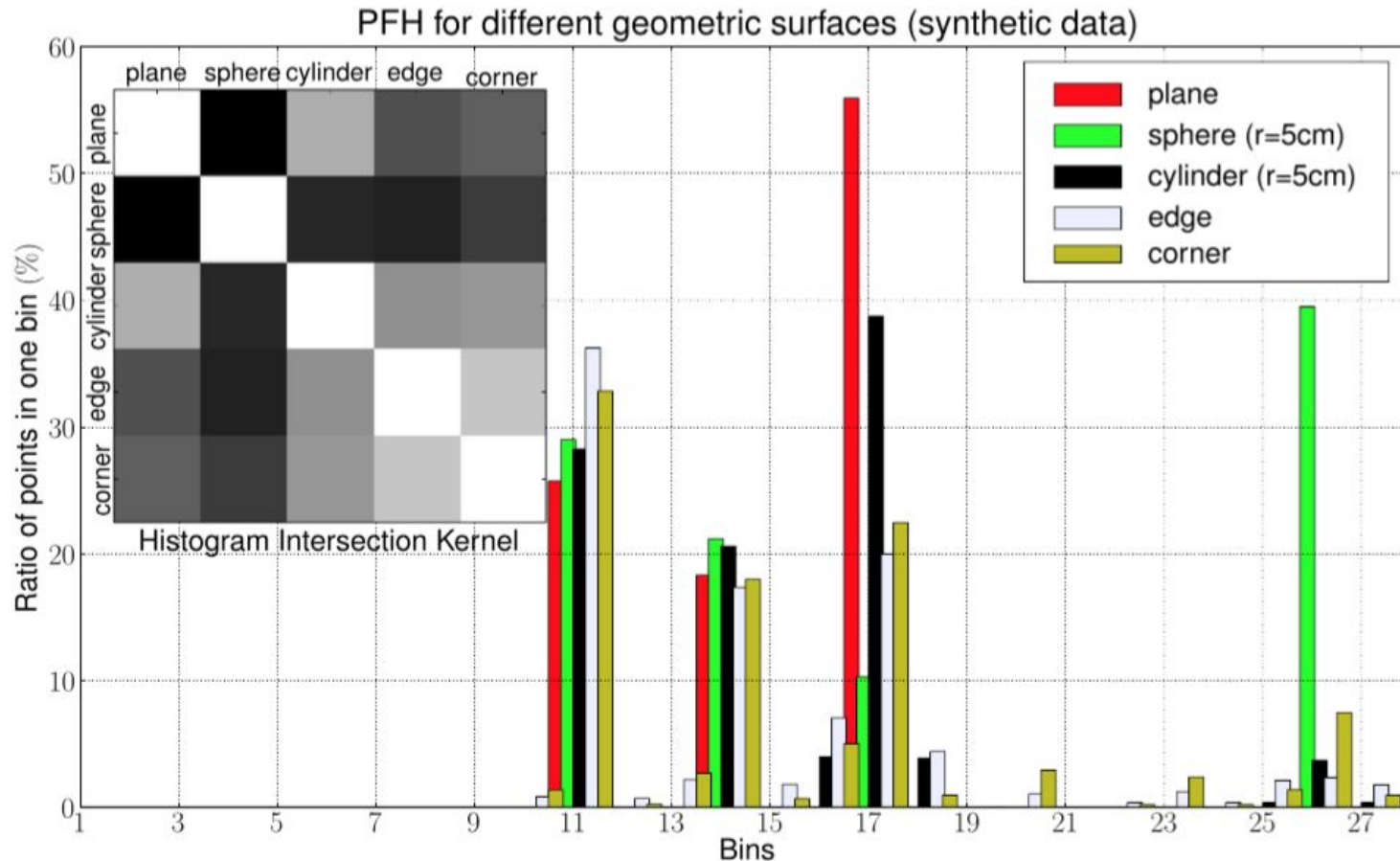
Density variations in points might affect how a PFH performs over different radii r_i, r_j

If $P_{\{f_i\}}$ signifies the set of persistent points at radii r_i , the full set of persistent points can be written as:

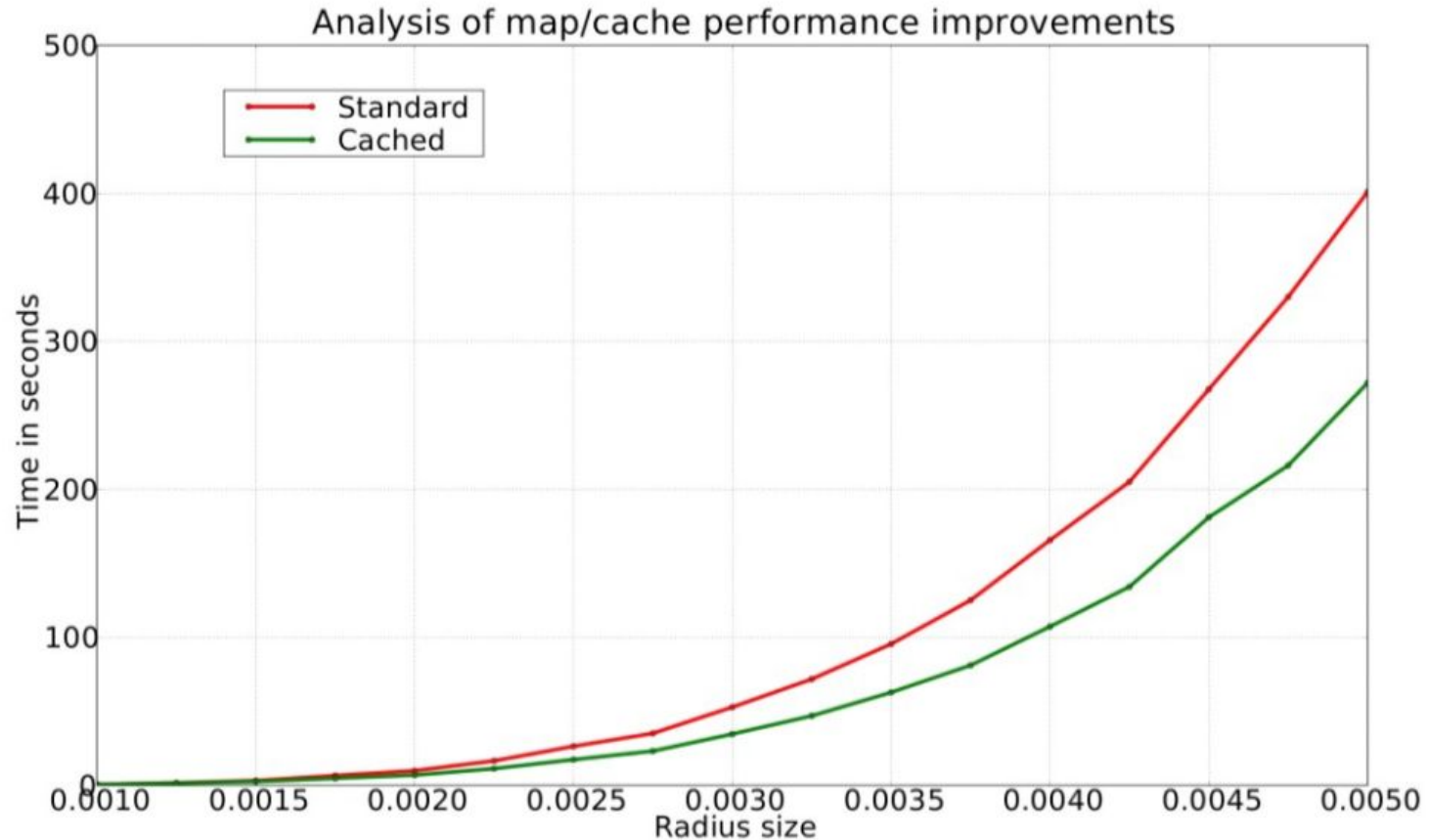
$$P_f = \bigcup_{i=1}^{n-1} [P_{f_i} \cap P_{f_{i+1}}]$$



Geometric Signatures



Caching and Point Ordering



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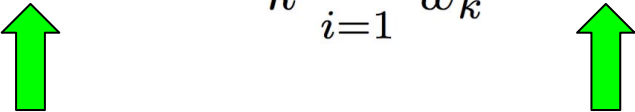
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Fast Point Feature Histograms

n points in a cloud, each with about k neighbors: $O(n \cdot k^2)$ to $O(n \cdot k)$ computation

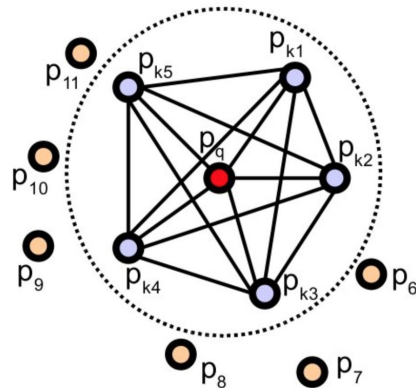
SPFH = Simplified Point Feature Histogram

$$FPFH(p) = SPFH(p) + \frac{1}{k} \sum_{i=1}^k \frac{1}{w_k} \cdot SPFH(p_k)$$


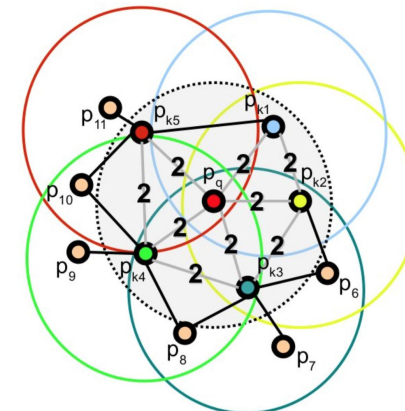
Contribution from p and neighbors $\leq r$

Contribution from p 's neighbors (points $\leq 2r$)

PFH



FPFH



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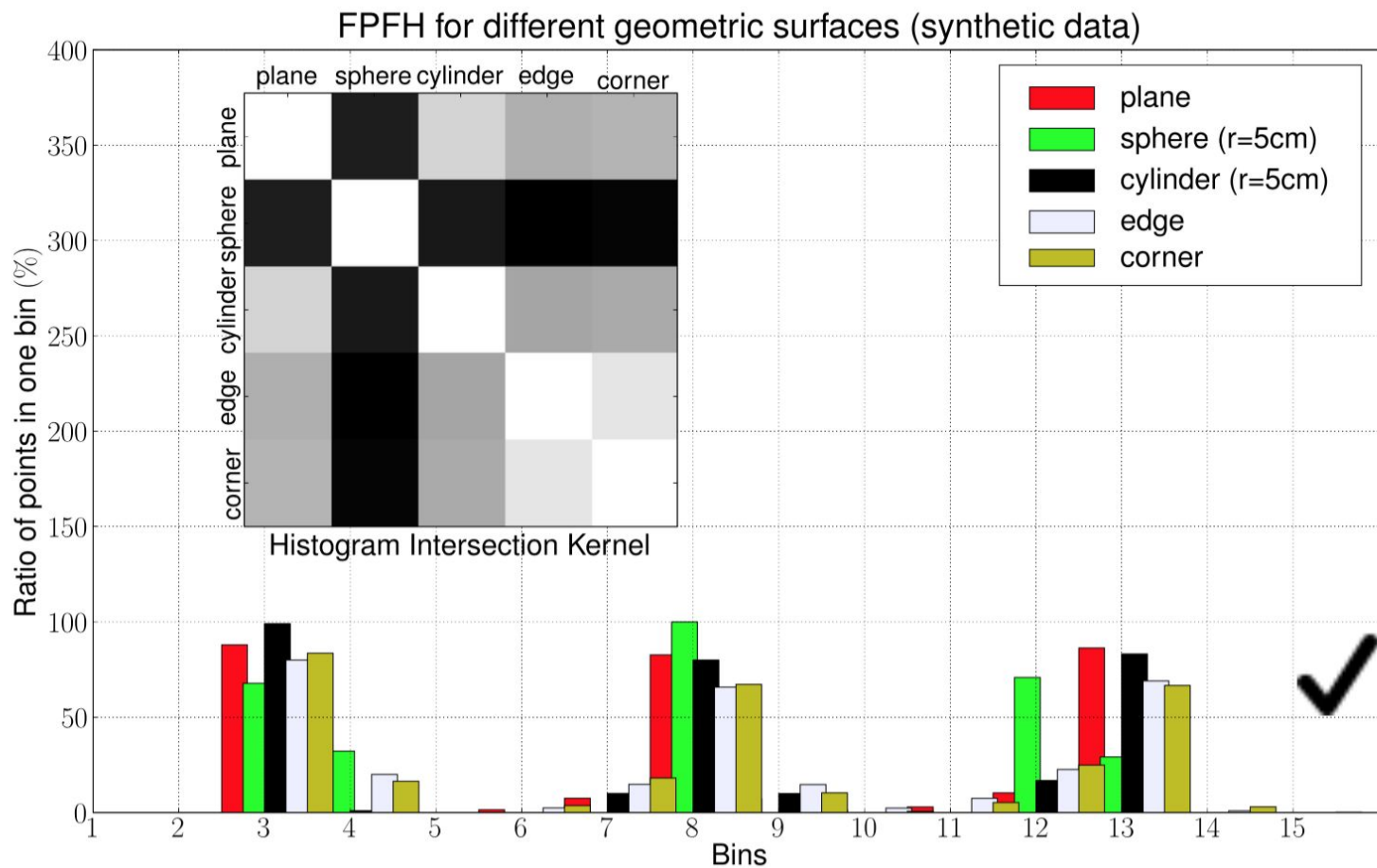
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FPFH Geometric Signatures



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Persistence Analysis

PFH



FPFH



Increasing radii from 0.003 - 0.005 cm



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Online Implementation

Scanline:



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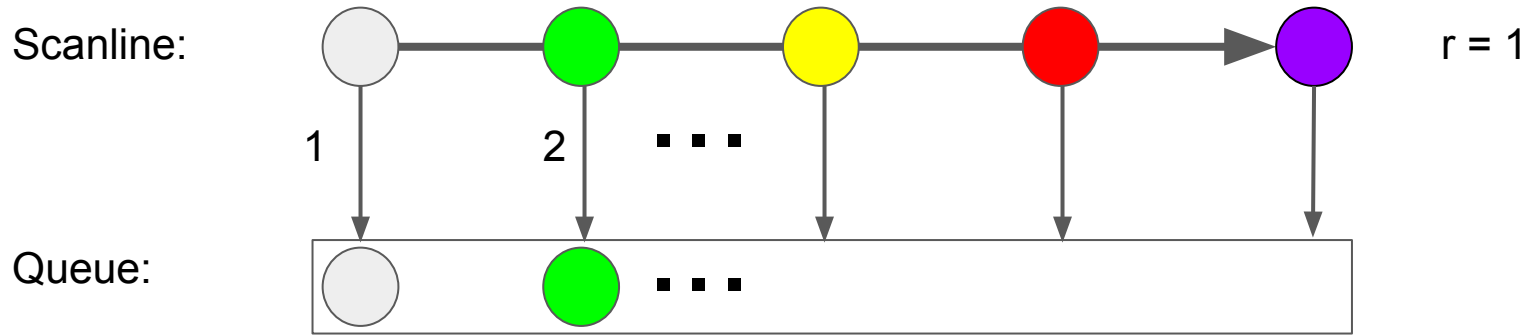
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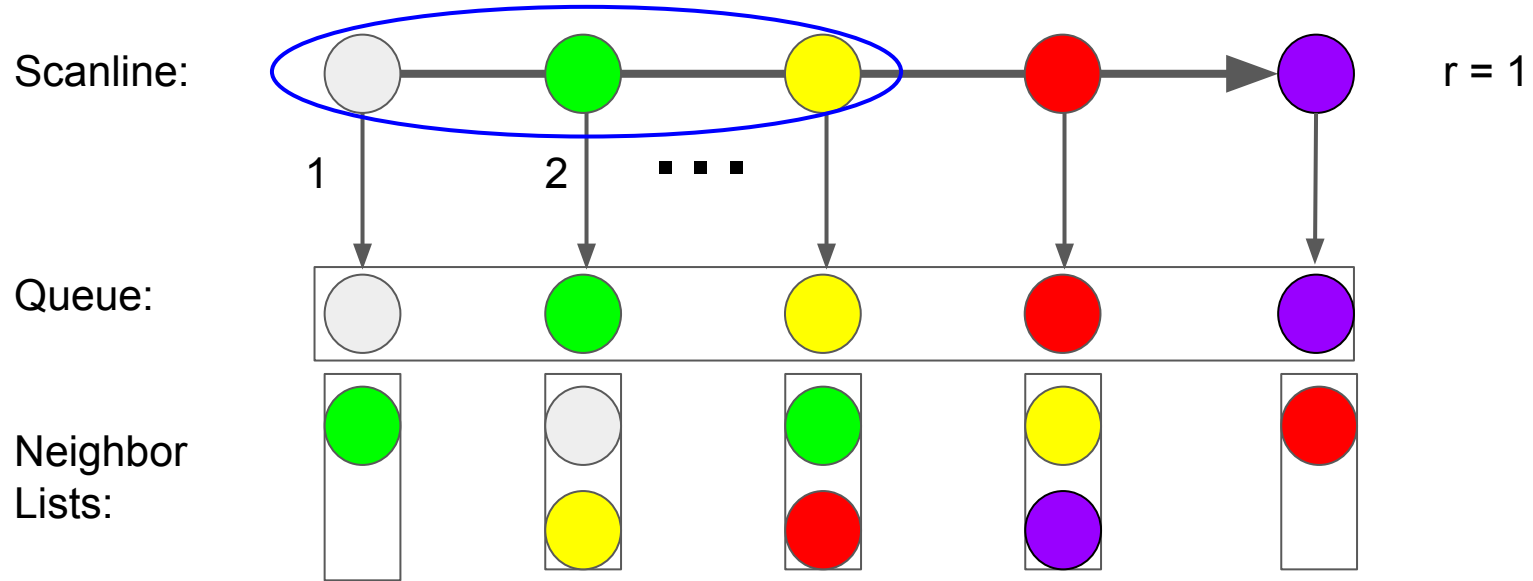
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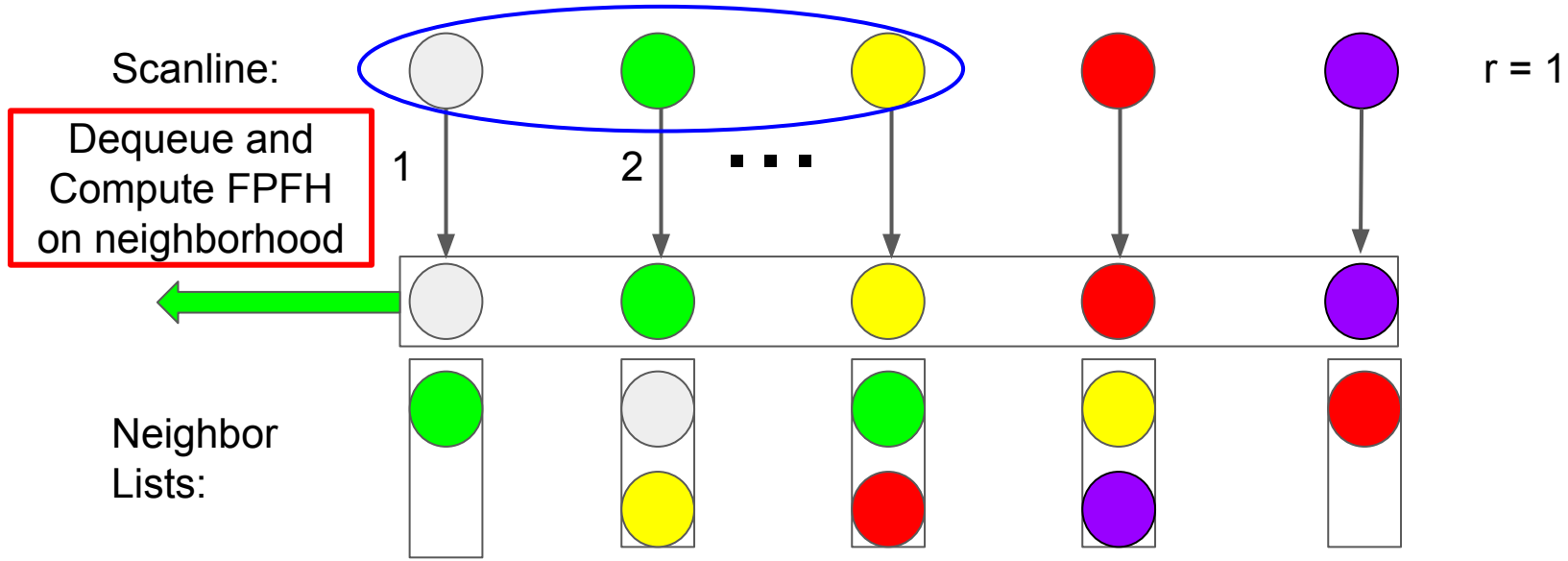
Online Implementation



Online Implementation



Online Implementation



Neighbor list of  will not be modified!



Sample Consensus Initial Alignment: SAC-IA

For point cloud initial registration

1. Select sample points s from a point cloud P that are at least a certain distance from each other, specified by a user as $d_{\{min\}}$
2. For each s , find a list of points in another cloud Q with a similar FPFH
3. Calculate a rigid transformation between points

The error metric defined is often used for the error between surfaces, and it is the **Huber Penalty** measure, L_h . The transformation with the lowest L_h is kept, and after a set number of iterations the algorithm terminates.

$$L_h(e_i) = \begin{cases} \frac{1}{2}e_i^2 & \|e_i\| \leq t_e \\ \frac{1}{2}t_e(2\|e_i\| - t_e) & \|e_i\| > t_e \end{cases}$$

Not specified how to choose t_e linear/quadratic boundary



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Experimental Results

	GIA - run 1	GIA - run 2	SAC-IA
run time	> 17 min	> 43 min	34 sec
# points considered	200	250	10462
# of combinations	37186	58300	1000

Datasets of outdoor scenes from a previous paper

GIA = Greedy Alignment Algorithm from previous work with FPFH
Searches through all possible correspondence pairs

SAC-IA: Considered more points, less combinations and in faster time

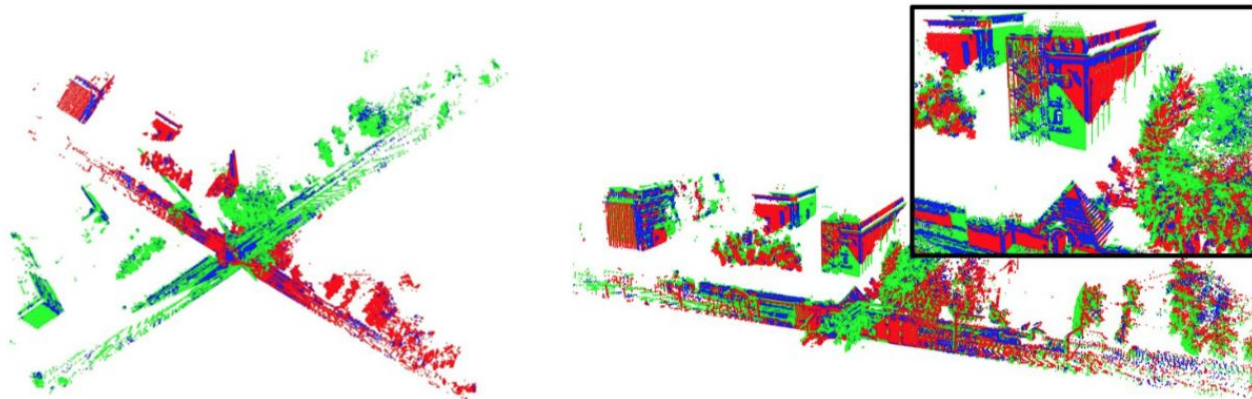


Conclusions

Good solution to finding an initial alignment to two point clouds, and can thus be refined using another algorithm (paper uses Levenberg-Marquadt from CIS 1)

Authors propose that they will investigate the robustness of the algorithm with noisier data in the future

Other uses for FPFH, like fast scene segmentation



Thoughts on Paper

Pros

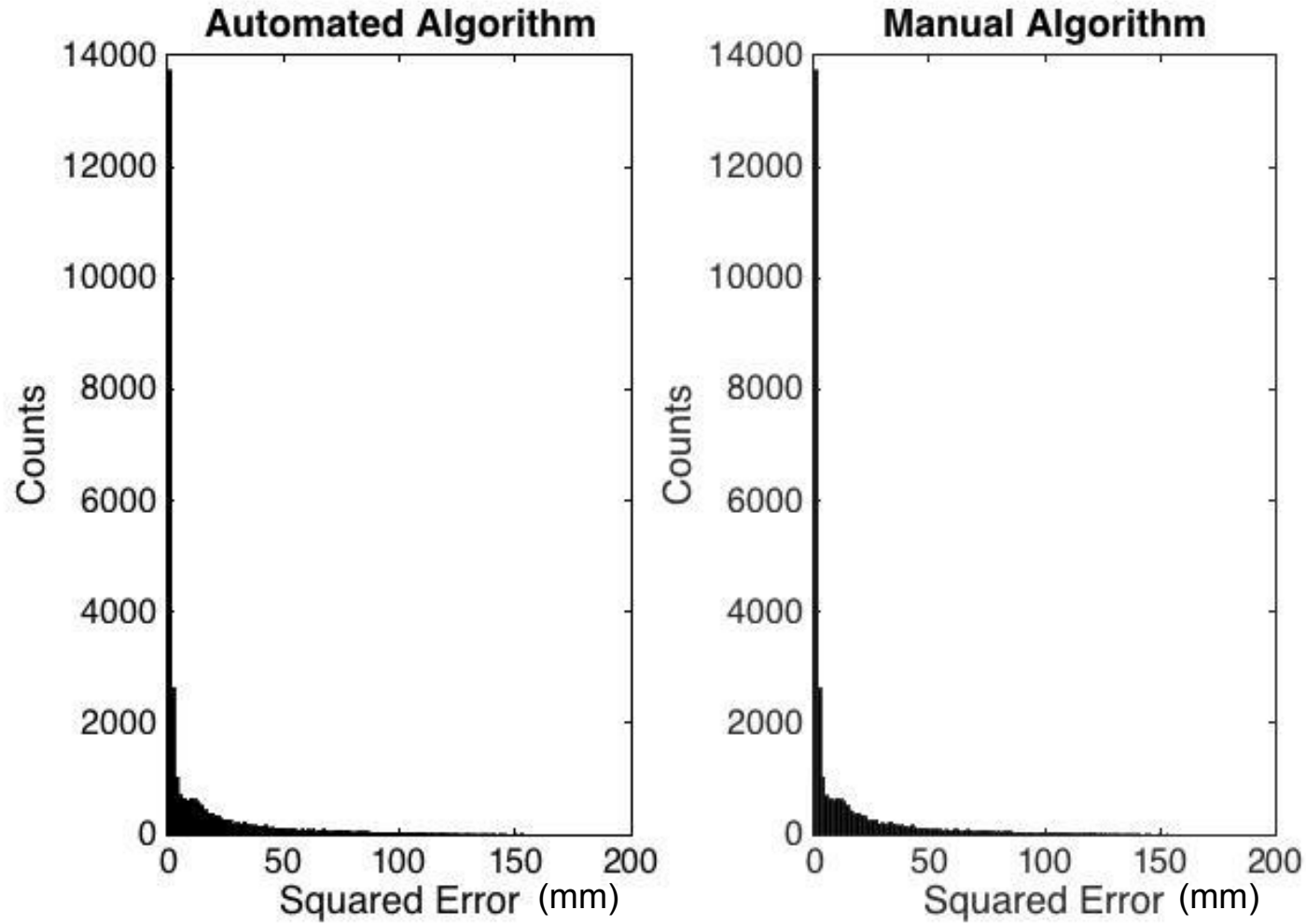
- Presents a solid conceptual understanding of using FPFH, and its advancements compared to its slower predecessor, PFH
- Proves why using features might be a good place for an initial alignment for two points clouds

Cons

- Quick comparison of an old algorithm (GIA) compared to a new algorithm (SAC-IA) using FPFH
- Does not compare the accuracy and precision of using FPFH for alignment, which is a large contributor for determining whether FPFH is a good algorithm to use
- Some confusing notation (utilizing SPF vs. SPFH)
- Too much reliance on old papers (decorrelation, histograms, half the paper was background)



Relevance



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Questions?



Reading List

Besl PJ, McKay ND. A Method for Registration of 3-D Shapes. IEEE Transactions on Pattern Analysis and Machine Intelligence, February 1992.

Lee SC, Fuerst B, Fotouhi J, Fischer M, Osgood G, Navab N. Calibration of RGBD Camera and Cone-Beam CT for 3D Intra-operative Mixed Reality Visualization. International Journal of Computer Assisted Radiology and Surgery / International Conference on Information Processing in Computer-Assisted Interventions (IPCAI), Heidelberg, June 2016.

Rusu RB, Cousins S. 3D is here: Point Cloud Library (PCL). IEEE International Conference on Robotics and Automation (ICRA), Shanghai, China, May 2011.

Rusu, RB, Marton ZC, Blodow N, Beetz M. Persistent Point Feature Histograms for 3D Point Clouds. Intelligent Autonomous Systems, Munich, Germany, December 2007.

Rusu RB, Blodow N, Beetz M. 2009. Fast point feature histograms (FPFH) for 3D registration. In Proceedings of the 2009 IEEE international conference on Robotics and Automation (ICRA'09). IEEE Press, Piscataway, NJ, USA, 1848-1853.

Wahl E, Hillenbrand U, Hirzinger G. Surflet-Pair-Relation Histograms: A Statistical 3D-Shape Representation for Rapid Classification. IEEE 3-D Digital Imaging and Modeling, Banff, Alta, October 2003.

