RGB-D HANDHELD MAPPING AND MODELING

MSc Dissertation

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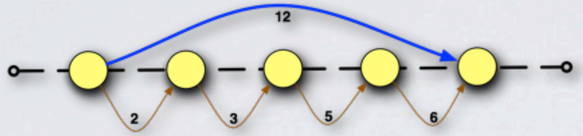
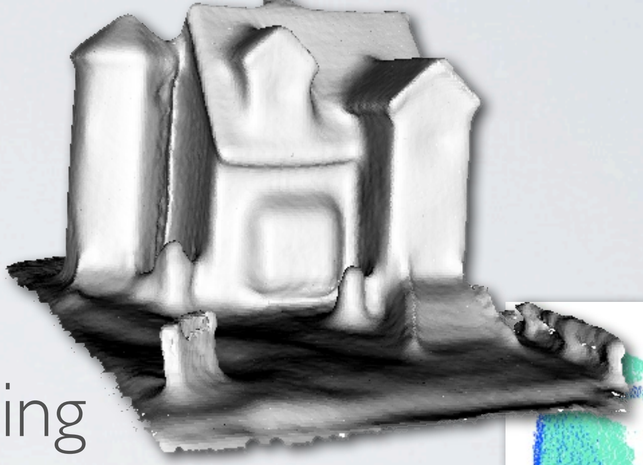
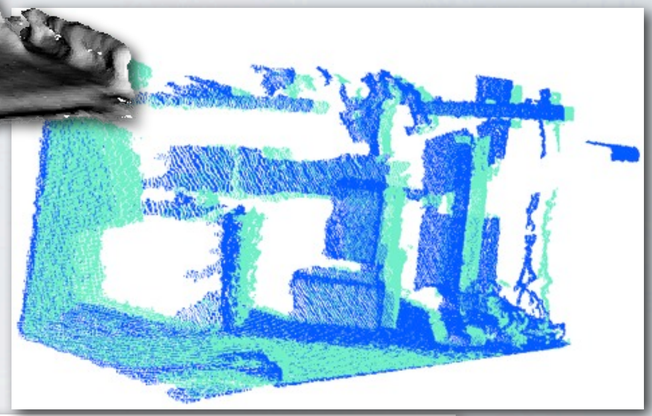
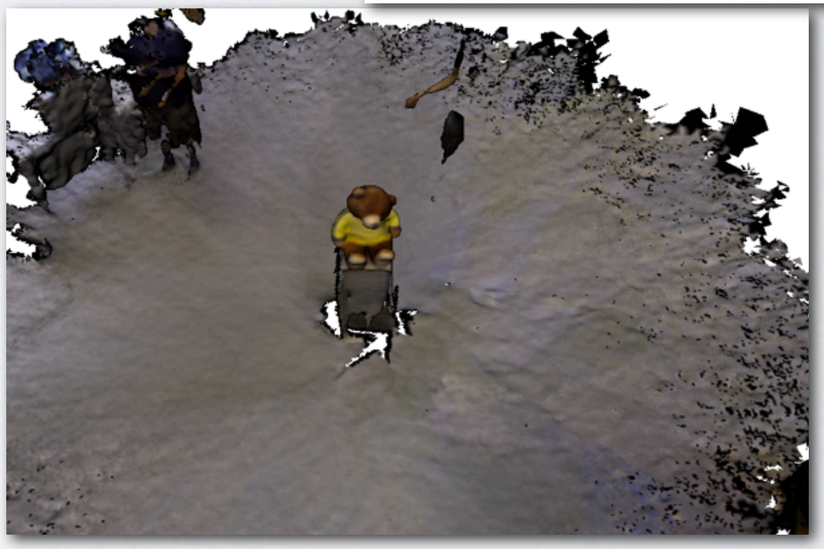


1. Introduction
2. Point Cloud Registration
3. Graph Optimization
4. Surface Reconstruction and Texture Mapping
5. Geometric Features
6. Results







Summary

- auto-exposure is bad for RGB features
- want a system that is independent of the lighting conditions and repeatable at any time of day
- indoor environments have repetitive textures - bad for localization
- want a coherent depth-only registration pipeline that can only improve by adding RGB information

Introduction - Why depth-only registration?

1. Incremental
   - Kinect Fusion
   - Kintinuous
2. perform loop closure
   - RGB-D Mapping variants
   - various commercial systems
3. with manual intervention

IZADI S., KIM D., HILLIGES O., MOLYNEAUX D., NEWCOMBE R., KOHLI P., SHOT- TON J., HODGES S., FREEMAN D., DAVISON A., FITZGIBBON A.: Kinectfusion: real-time 3d reconstruction and interaction using a moving depth camera. In Proceedings of the 24th annual ACM symposium on User interface software and technology (New York, NY, USA, 2011), UIST '11, ACM, pp. 559–568.

WHELAN T., JOHANNSSON H., KAESS M., LEONARD J., MCDONALD J.: Robust Tracking for Real-Time Dense RGB-D Mapping with Kintinuous. Tech. Rep. MIT- CSAIL-TR-2012-031, Computer Science and Artificial Intelligence Laboratory, MIT, Sep 2012.

HENRY P., KRAININ M., HERBST E., REN X., FOX D.: Rgbd mapping: Using depth cameras for dense 3d modeling of indoor environments. In In RGB-D: Advanced Reasoning with Depth Cameras Workshop in conjunction with RSS (2010).

STURM J., ENGELHARD N., ENDRES F., BURGARD W., CREMERS D.: A benchmark for the evaluation of rgb-d slam systems. In Proc. of the International Conference on Intelligent Robot Systems (IROS) (Oct. 2012).

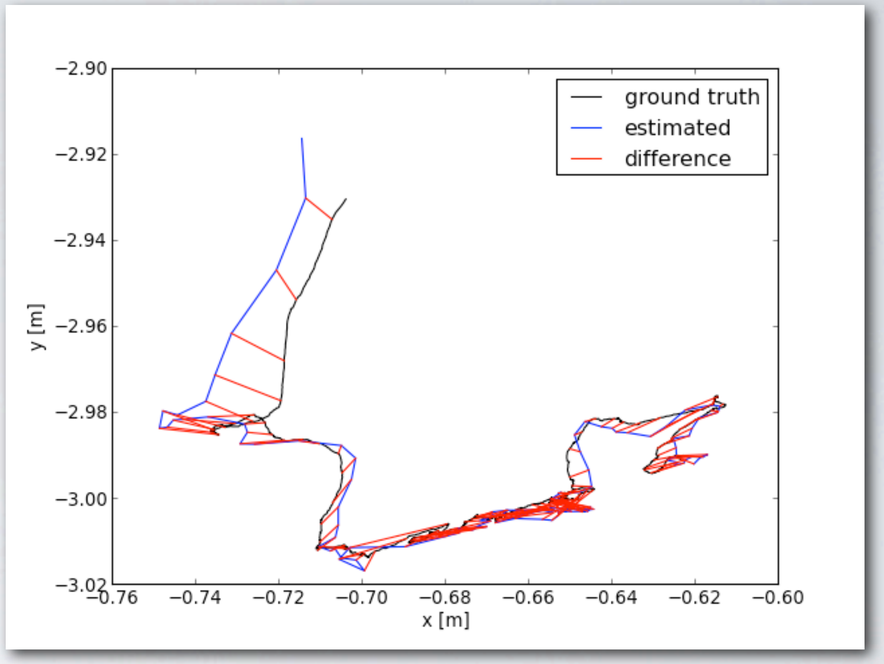
PITZER B., KAMMEL S., DUHADWAY C., BECKER J.: Automatic reconstruction of textured 3d models. In IEEE International Conference on Robotics and Automa- tion, ICRA 2010, Anchorage, Alaska, USA, 3-7 May 2010 (2010), IEEE, pp. 3486– 3493.

DU H., HENRY P., REN X., CHENG M., GOLDMAN D. B., SEITZ S. M., FOX D.: Interactive 3d modeling of indoor environments with a consumer depth camera. In Proceedings of the 13th international conference on Ubiquitous computing (New York, NY, USA, 2011), UbiComp '11, ACM, pp. 75–84.

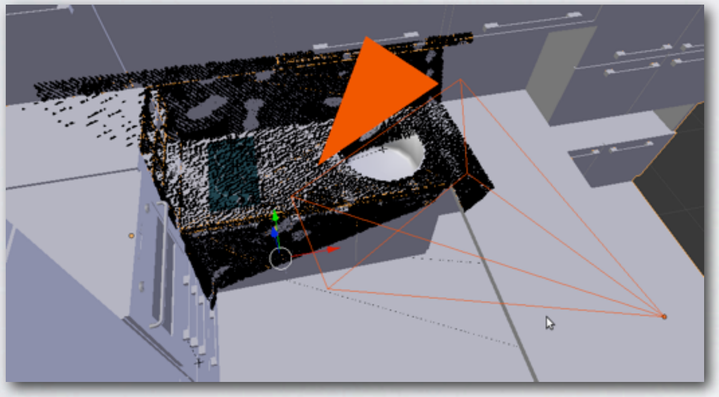
Similar Systems

Room modeling, outside modeling,
object modeling - various sizes

TUM Datasets - with ground truth transformations

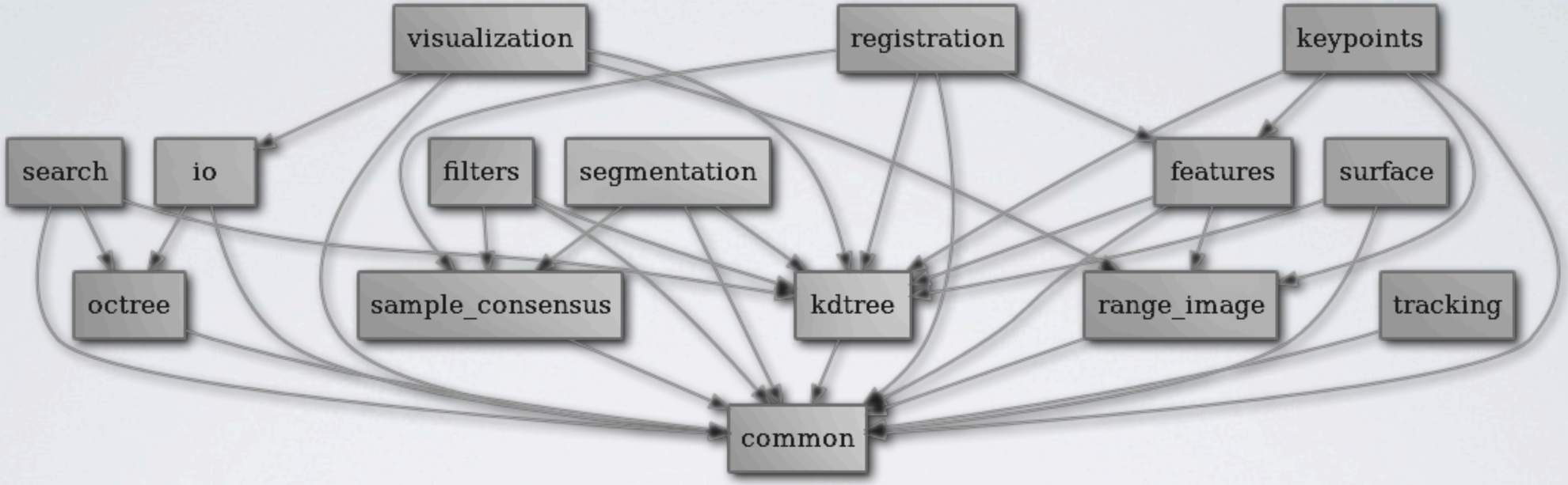


Blensor



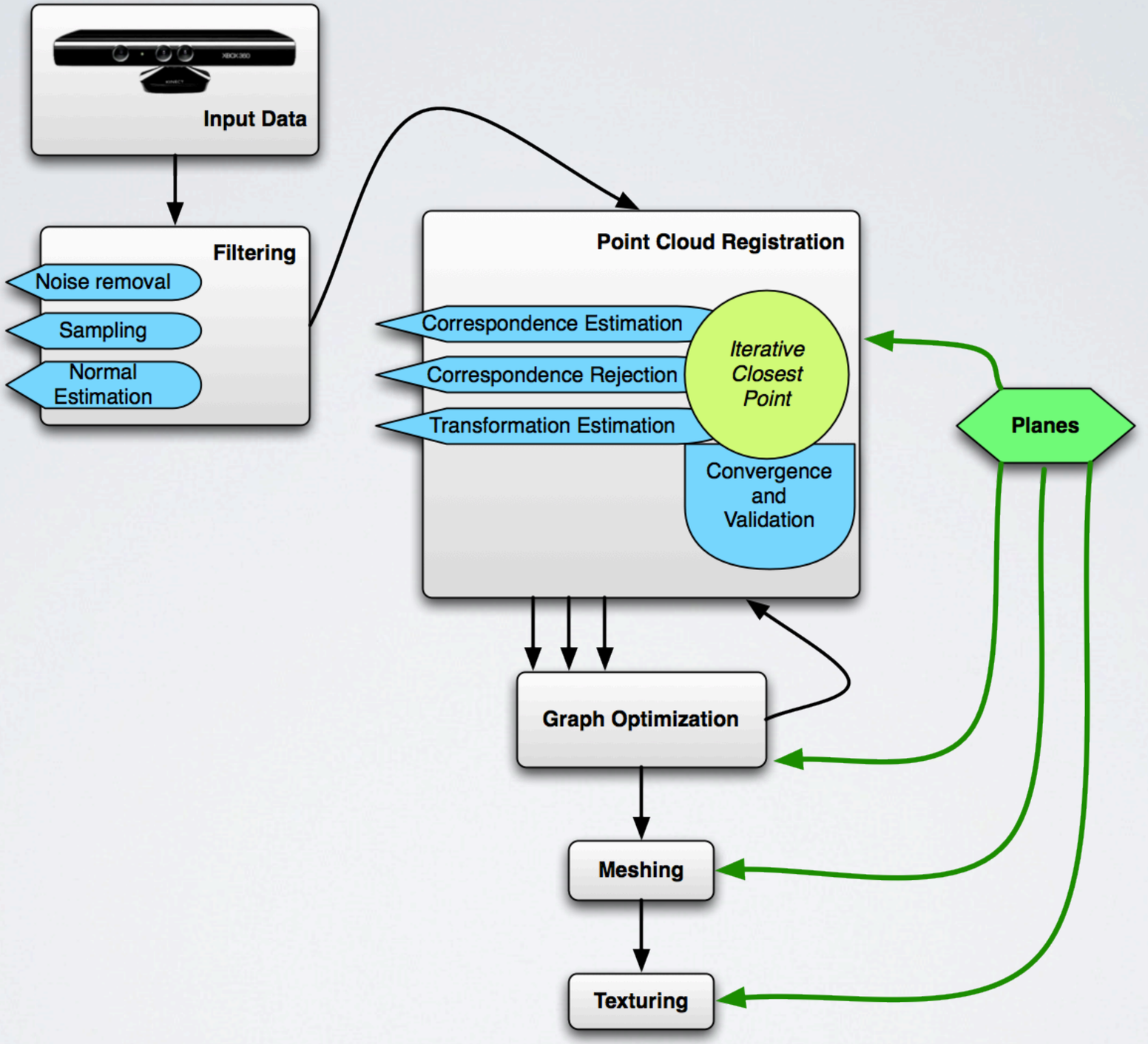
Our own

Datasets



pointcloudlibrary

Open Source Software


Input Data
Filtering
Noise removal
Sampling
Normal Estimation
Point Cloud Registration
Correspondence Estimation
Correspondence Rejection
Transformation Estimation
Iterative Closest Point
Convergence and Validation
Planes
Graph Optimization
Meshing
Texturing

Experiments on combinations of algorithms for the steps of the ICP algorithm:

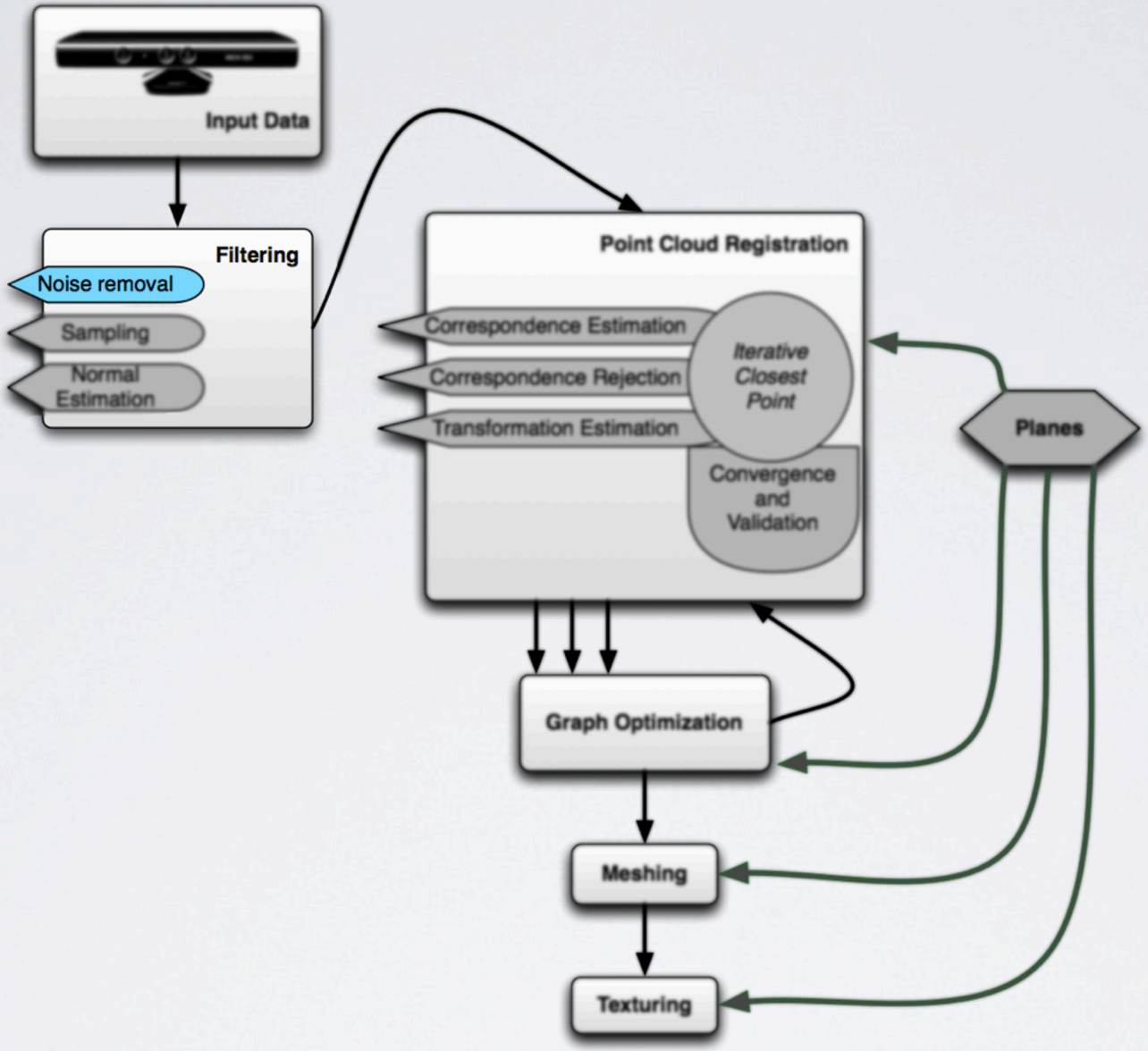
- random sampling
- closest point correspondence
- filter correspondences based on normals
- constant weighting of point pairs
- point-to-plane error metric

Baseline

- random sampling
- projection-based pairing
- constant weighting of point pairs
- point-to-plane error metric

Best

RUSINKIEWICZ S., LEVOY M.: Efficient variants of the ICP algorithm. In Third International Conference on 3D Digital Imaging and Modeling (3DIM) (June 2001).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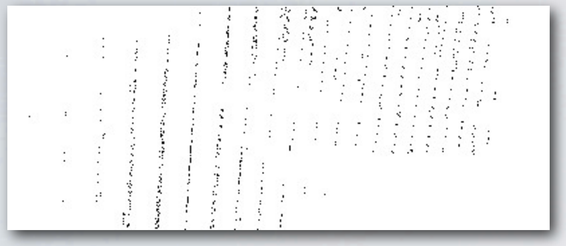
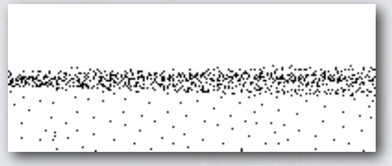




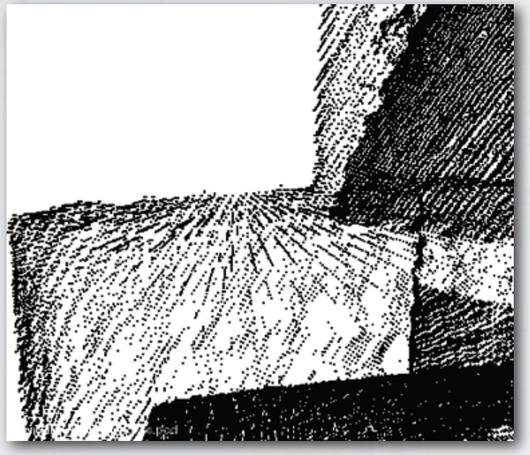
RGB-D
camera noise

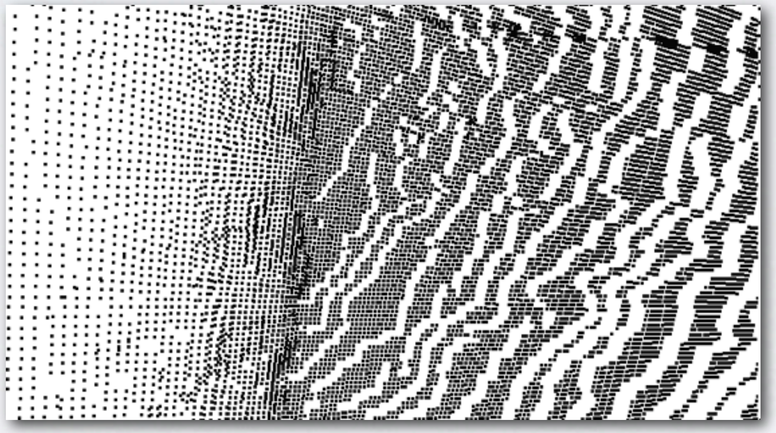
$$\sigma_L(\theta)[px] = 0.8 + 0.035 * \frac{\theta}{\pi/2-\theta}$$

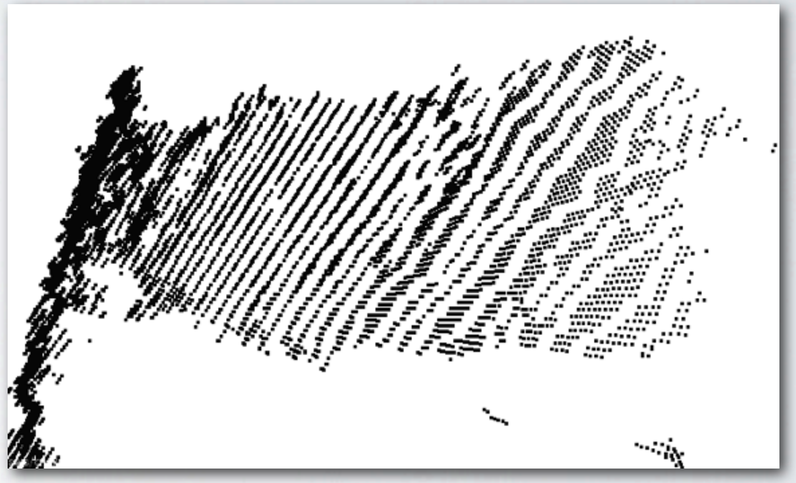
$$\sigma_L(\theta)[m] = \sigma_L(\theta)[px] * z * p_x / f_x$$

$$\sigma_z(z,\theta) = 0.0012 + 0.0019 * (z-0.4)^2, \text{ when } 10^\circ \leq \theta \leq 60^\circ$$

Noise
model



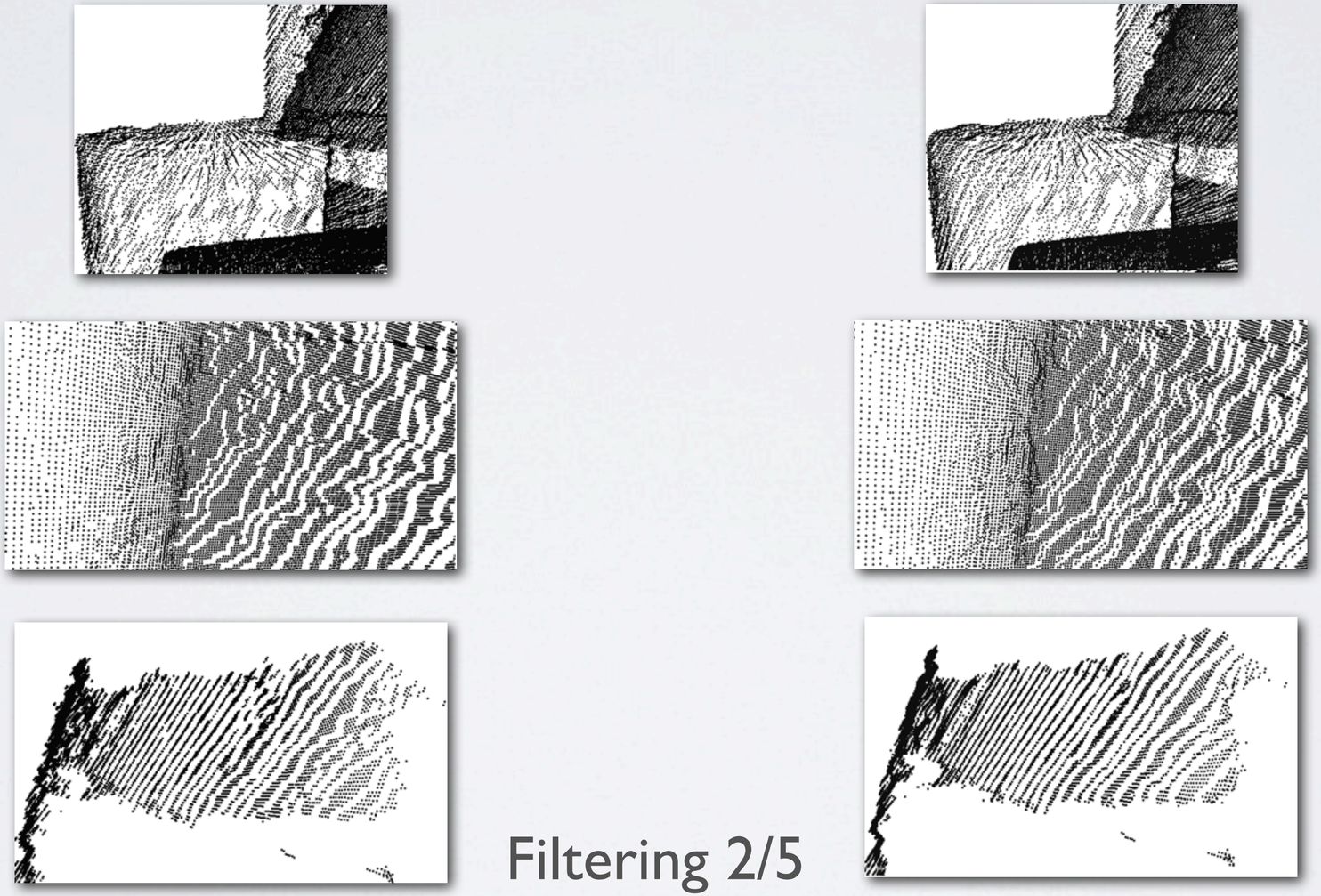




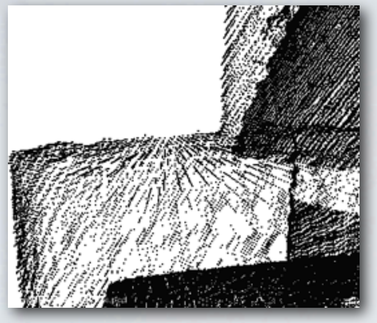
Filtering 1/5

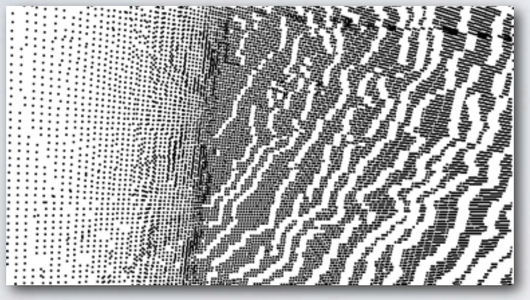
Median filter

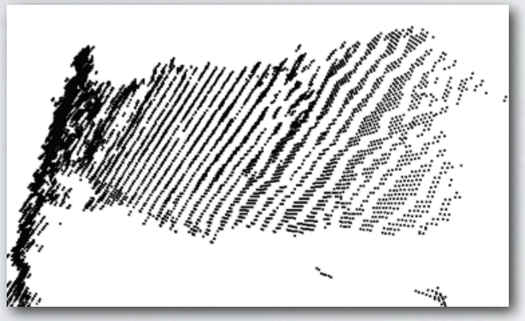
- simple image processing filter
- good for impulse noise
- fixed size window - take median



Bilateral filter smooths the signal and preserves strong edges





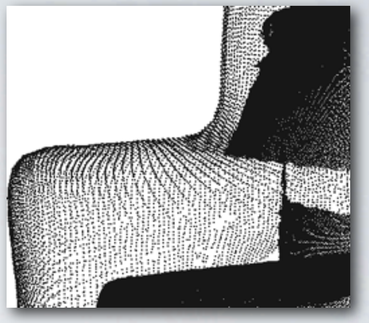


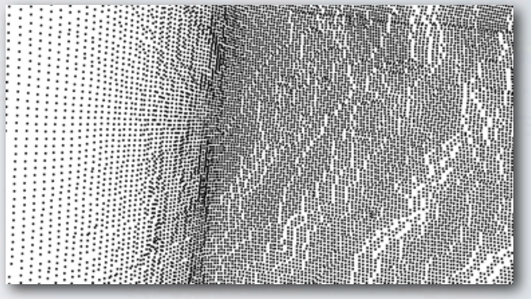
one image:

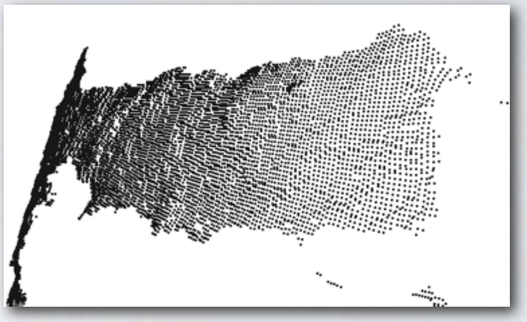
$$\tilde{I}_p = \frac{\sum_{s \in \mathcal{N}} f(p-s) * g(I_p - I_s) * I_s}{\sum_{p \in \mathcal{N}} f(p-s) * g(I_p - I_s)}$$

two images (depth + RGB):

$$\tilde{S}_p = \frac{\sum_{q \in \mathcal{N}} S_q * f(||p-q||) * g(||I_p - I_q||)}{\sum_{q \in \mathcal{N}} f(||p-q||) * g(||I_p - I_q||)}$$







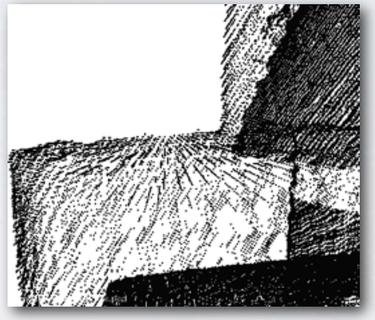
* fast implementation by interpreting the image as a 3D function the filter becomes a convolution in 3D

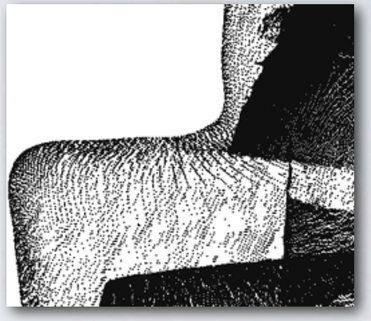
PARIS S., DURAND F.: A fast approximation of the bilateral filter using a signal processing approach. Int. J. Comput. Vision 81, 1 (Jan. 2009), 24–52.

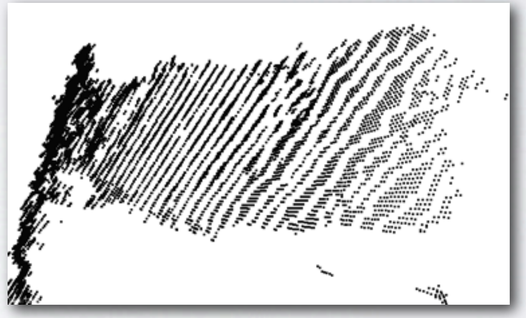
Moving Least Squares

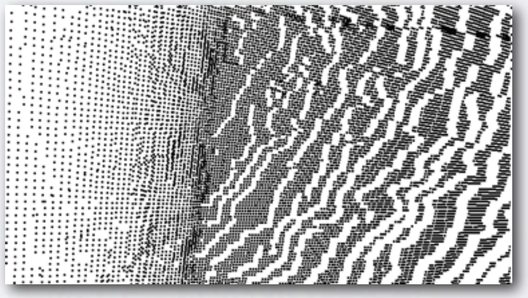
- fit a plane locally with PCA
- fit a 2D function on the plane
- project the point onto the function

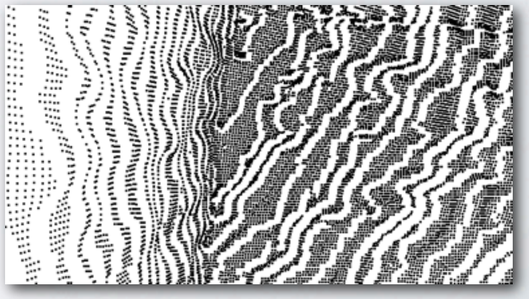
$$\sum_{i=1}^{N} [g(x_i, y_i) - n \circ (p_i - q)]^2 * \theta(||p_i - q||)$$









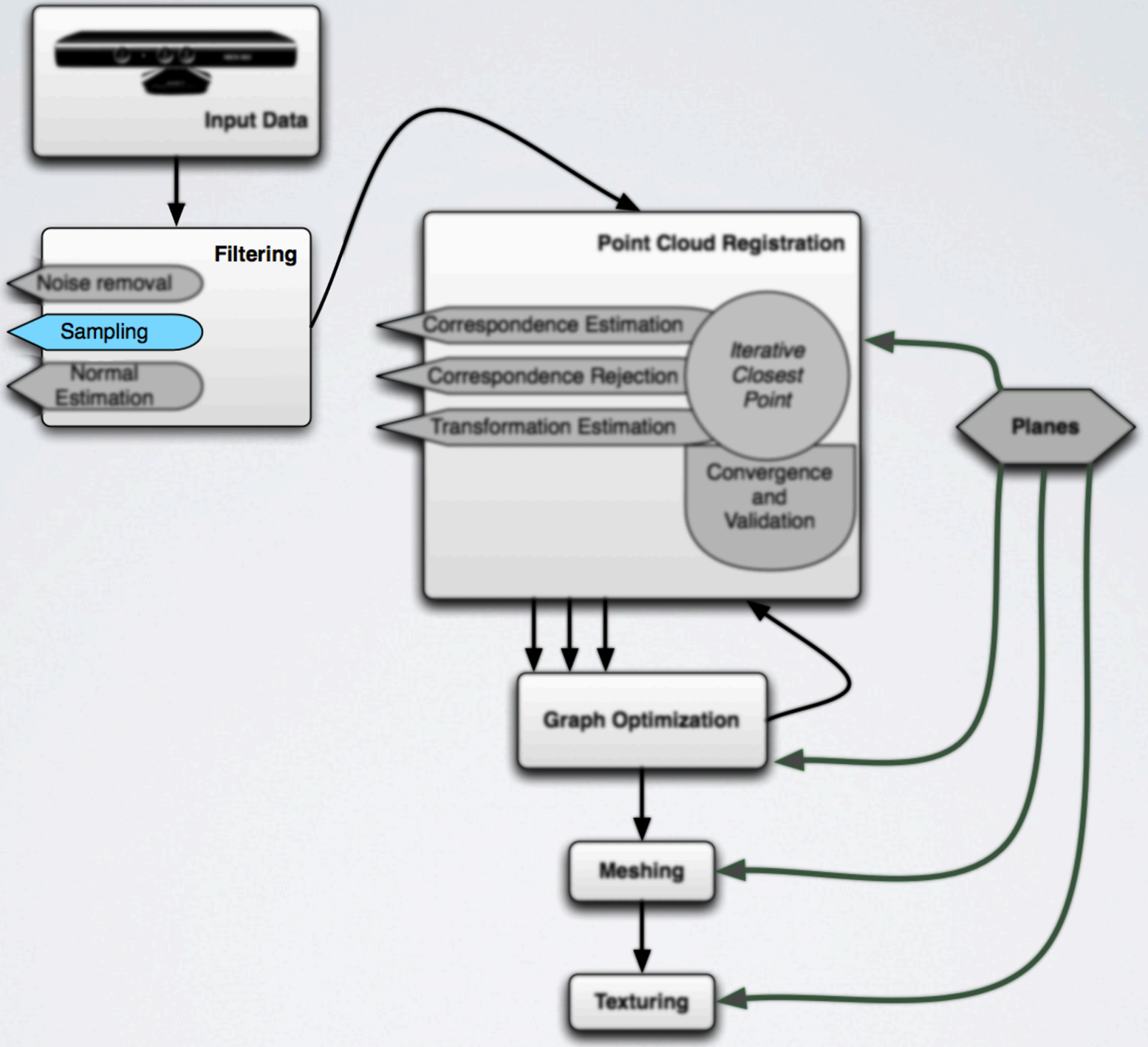


- Do not do it for all the point in the cloud, but for a voxel grid-ed version
- allows for up-sampling and uniform point distribution

ALEXA M., BEHR J., COHEN-OR D., FLEISHMAN S., LEVIN D., SILVA C. T.: Com- puting and rendering point set surfaces. IEEE Transactions on Visualization and Computer Graphics 9 (2003), 3–15.

Cloud	RMSE original Simulated Noise [cm]	RMSE Bilateral Filter [cm]	RMSE MLS [cm] Filter [cm]	RMSE Median Filter [cm]
1	18.219	17.465	17.672	17.457
2	19.730	19.092	19.123	19.147
3	17.066	16.782	16.665	16.436
4	17.259	17.173	16.756	16.475
5	11.542	11.533	11.197	10.938

Filtering 5/5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- use all the points
- uniform sampling
- random sampling
- normal space sampling
- sample points on color edges

Rusinkiewicz et al. - best

- covariance sampling

new

RUSINKIEWICZ S., LEVOY M.: Efficient variants of the ICP algorithm. In Third International Conference on 3D Digital Imaging and Modeling (3DIM) (June 2001).

- use all the points
- uniform sampling
- random sampling

very similar results
advantage of random - force to choose different pairs at each iteration

- **normal space sampling**

  place normals into m3 bins
  randomly (uniform) select samples from each bin
  => uniformly cover the half-sphere of normals for each scan

sample points so that the transformation is "locked" better
the sampled cloud needs to have all the eigenvalues of the covariance matrix equal

- **covariance sampling**

iterative algorithm - sort points by contribution to each eigenvalue, and select the smallest to balance the eigenvalues

$$\Delta d_i = [\Delta r^T \; \Delta t^T] \begin{bmatrix} p_i \times n_i \\ n_i \end{bmatrix}$$

each point has a translational force and a rotation torque

$$C = FF^T = \begin{bmatrix} p_1 \times n_1 & \dots & p_k \times n_k \\ n_1 & \dots & n_k \end{bmatrix} \begin{bmatrix} (p_1 \times n_1)^T & n_1^T \\ \dots & \dots \\ (p_k \times n_k)^T & n_k^T \end{bmatrix}$$

the covariance matrix tells us about the stability of the registration

not full rank => transform is not unique

want a condition number close to 1

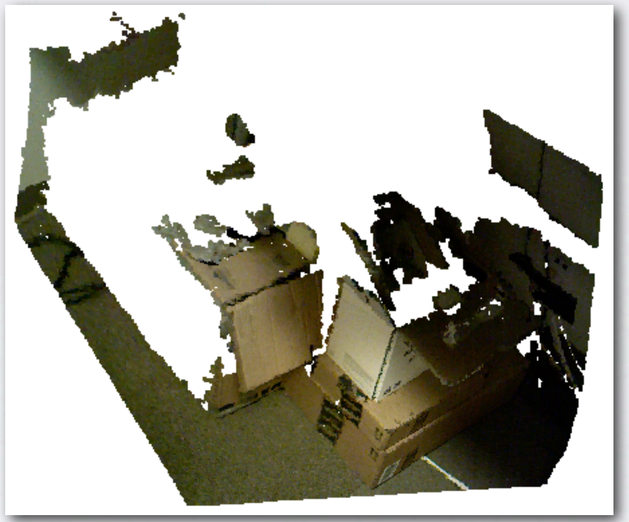
condition number !!!

single wall 2946

two walls 862.45

room corner 10.27

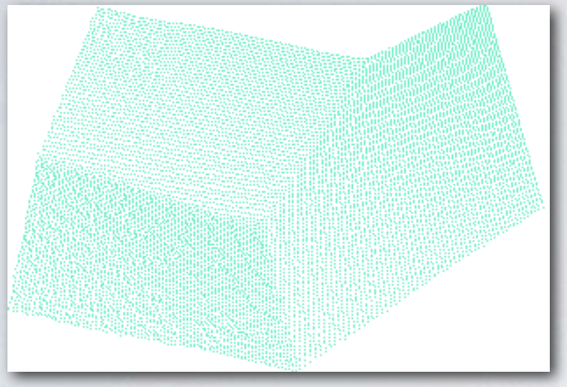
desk clutter 12.83



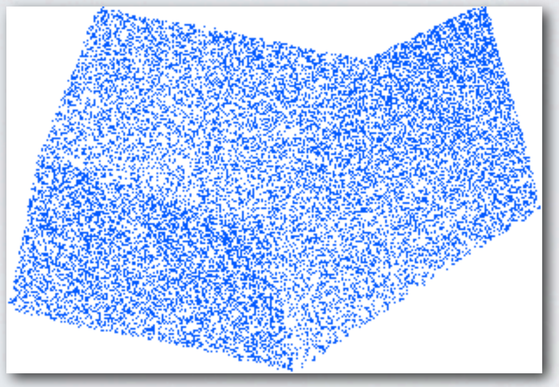
boxes 4.58

Sampling 5/7

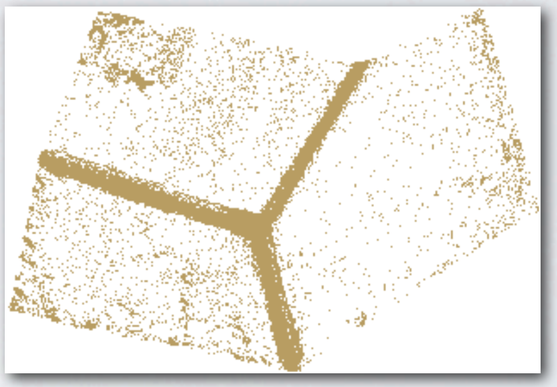
condition number !!!



uniform



random



normals

covariance

Scan	Condition number				
	input	uniform	random	normal	covariance
single wall	2946.26	2910.05	2959.42	498.65	635.89
two walls	862.45	1099.66	824.77	98.47	101.21
room corner	10.27	10.27	10.31	7.7	6.97
desk clutter	12.83	13.10	12.91	6.89	21.36
boxes	4.58	4.59	4.73	3.32	9.33

Amount of subsampling

HENRY P., KRAININ M., HERBST E., REN X., FOX D.: Rgbd mapping: Using depth cameras for dense 3d modeling of indoor environments. In In RGB-D: Advanced Reasoning with Depth Cameras Workshop in conjunction with RSS (2010).

uniform sampling - 25% - 10% of the initial size => 75k-30k points

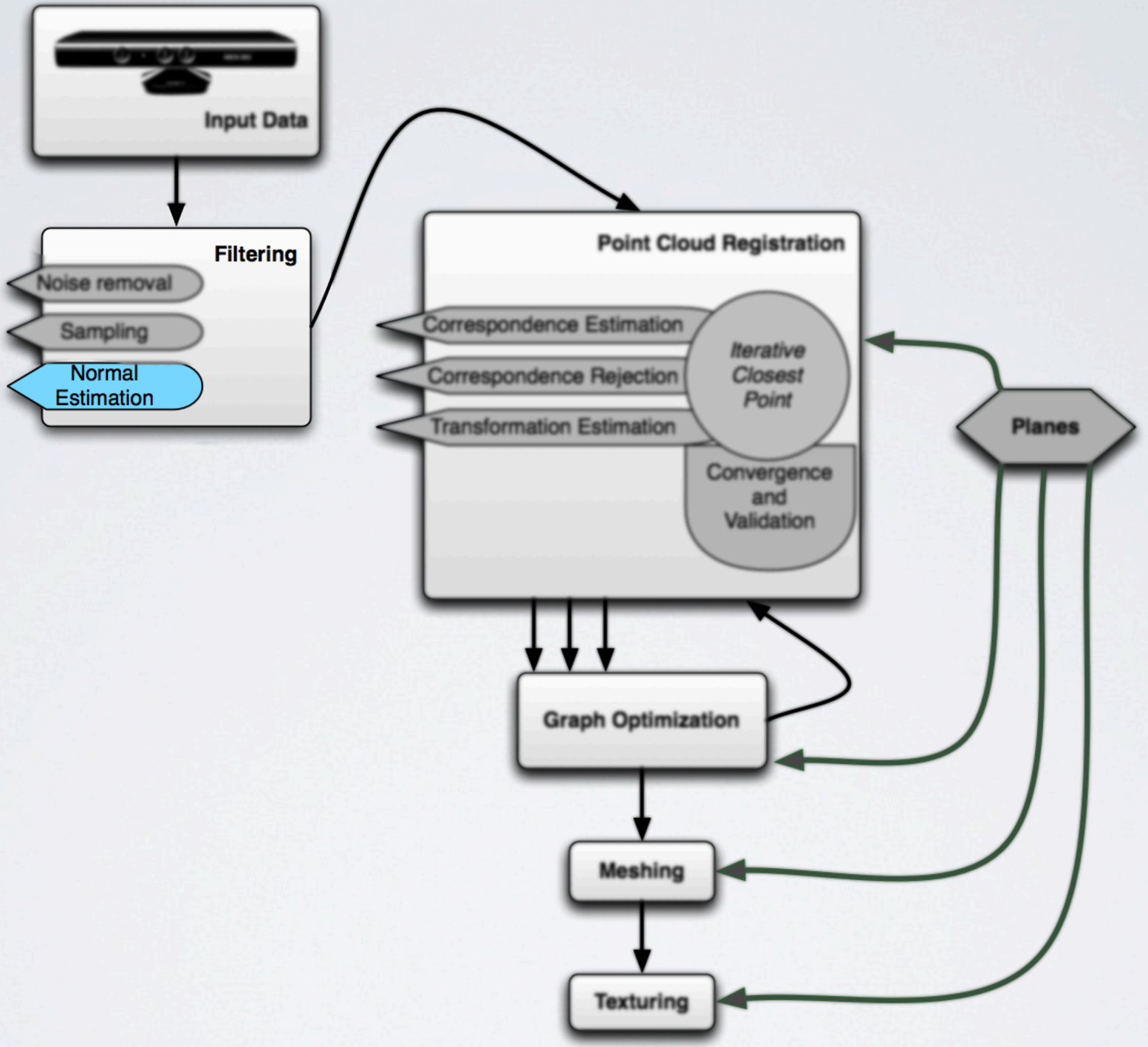
POMERLEAU F., MAGNENAT S., COLAS F., LIU M., SIEGWART R.: Tracking a depth camera: Parameter exploration for fast icp. In Proc. of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (2011).

complex sampling techniques are too slow compared to the performance improvement

uniformly subsample the depth grid to 6.25% of the initial size (19.2k points) and then random subsample to 1% (3.7k points)

The number of points is the factor that influences performance the most!

Tuning the sampling rate is essential for real-time systems!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3D sensors create sample locations, and lose information about the surfaces

- averaging methods
- optimization-based methods

weighting:

- angles
- area
- centroid
- gravitational

- PlaneSVD — fit a plane in the local neighborhood, minimize the error with SVD

- PlanePCA — minimize the variance of the points by computing a local coordinate system

superior

Computation time: seconds

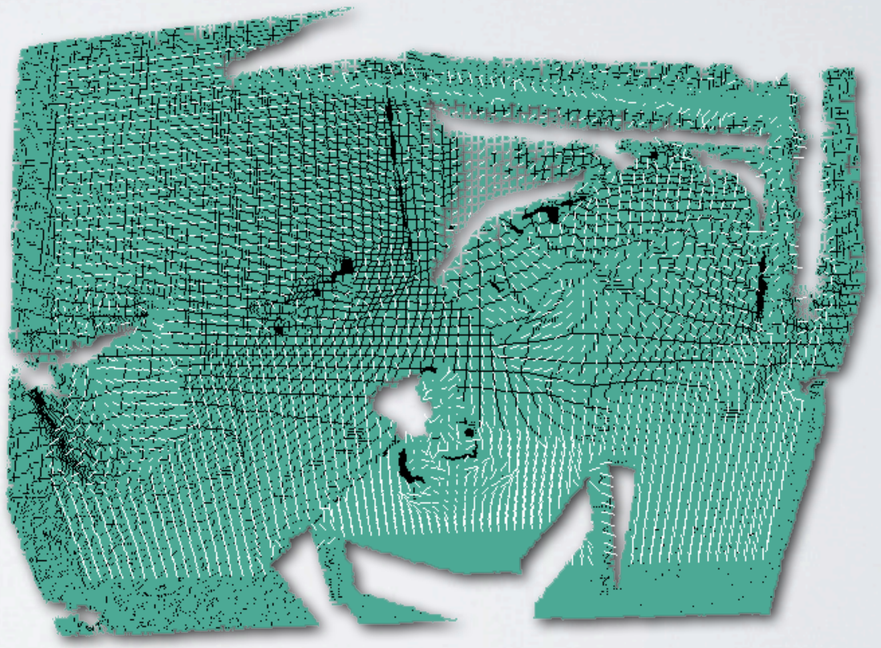
KLASING K., ALTHOFF D., WOLLHERR D., BUSS M.: Comparison of surface normal estimation methods for range sensing applications. In Proceedings of the 2009 IEEE international conference on Robotics and Automation (Piscataway, NJ, USA, 2009), ICRA'09, IEEE Press, pp. 1977–1982.

Normal Estimation 1/2

Normal Estimation using integral images

- smooth the data with a variable window size depending on the depth
- mask for depth changes
- compute the normals as cross products of grid neighbors - adaptive window

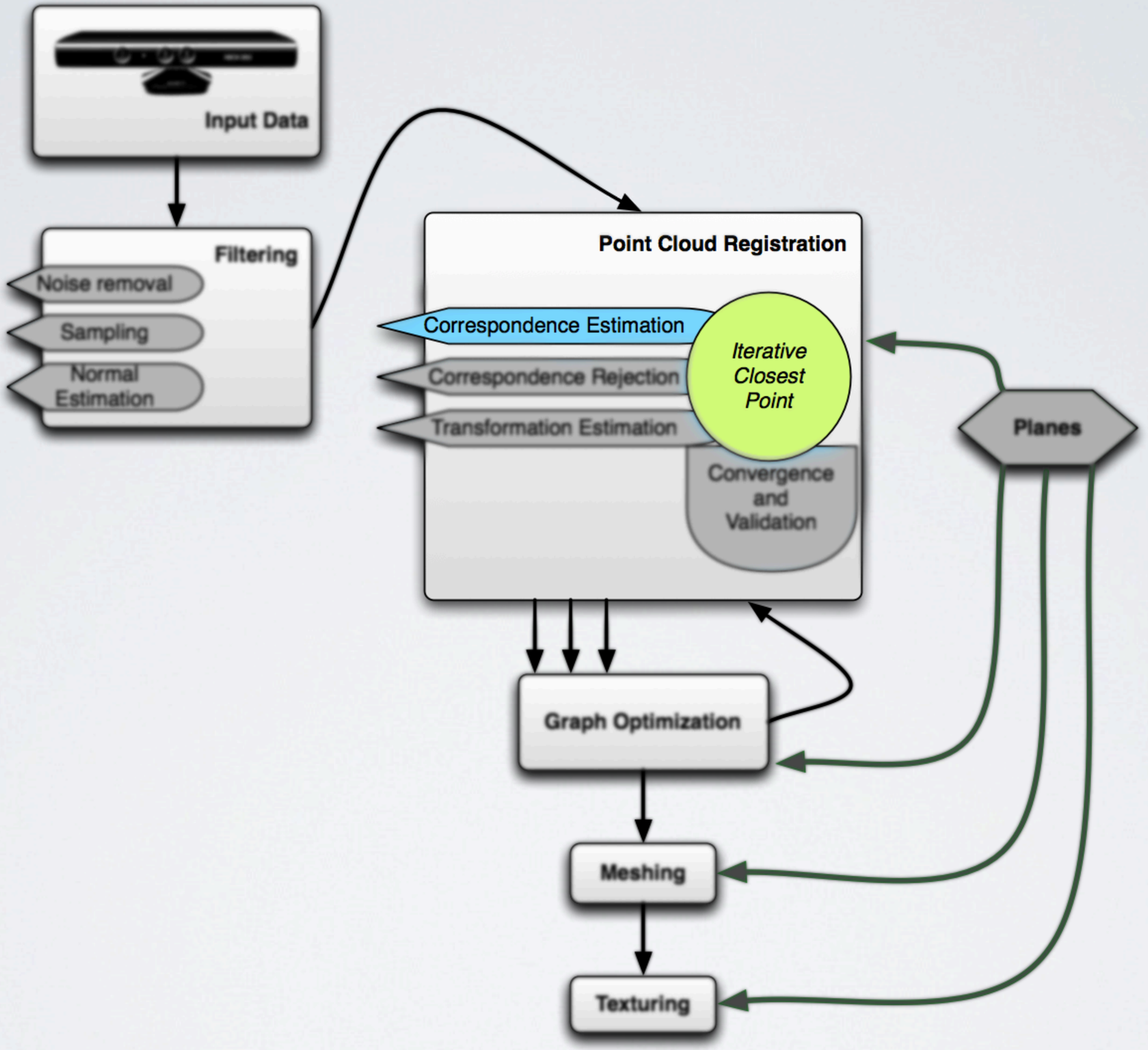
Authors claim better results than PlanePCA



Downside: cannot compute normals near the image borders

Computation time: ~50 ms

Normal Estimation 2/2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- projection-based

$$\begin{bmatrix} f_x & 0 & c_x & 0 \\ 0 & f_y & c_y & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} P_x \\ P_y \\ P_z \\ 1 \end{bmatrix} = \begin{bmatrix} d \cdot u \\ d \cdot v \\ d \end{bmatrix}$$

bad when the transformation is large

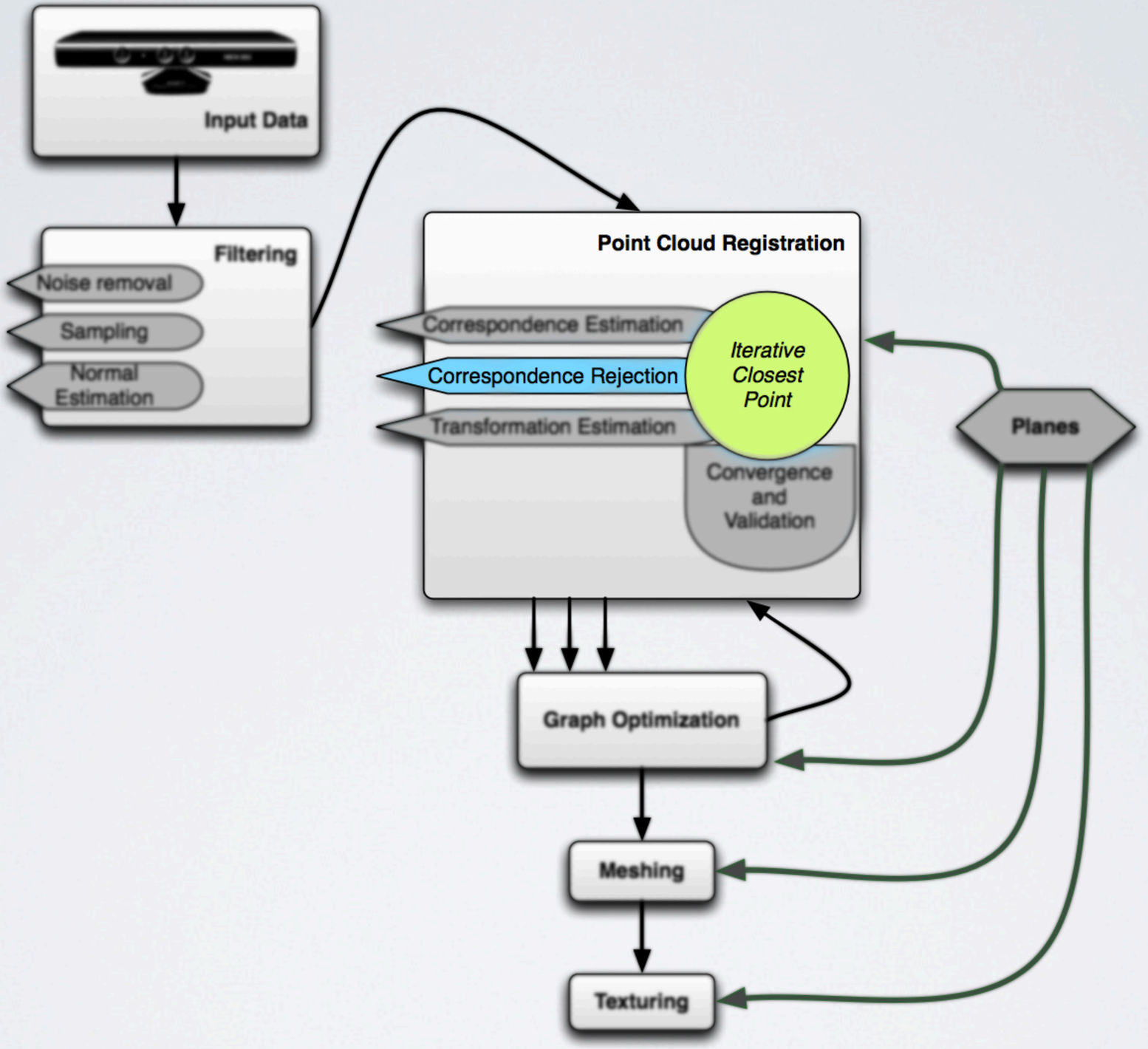
- search-based
  - exhaustive O(N)
  - kd-tree

Long init times O(N logN),
but fast search times O(logN)

Cloud size	Naive search [ms]	Kd-tree		Projection-based [ms]
		init [ms]	search [ms]	
307 200	35045	106	660	3
76800	2188	23	130	1
19200	139	5	25	1
4800	8	1	6	1

Timing

Correspondence Estimation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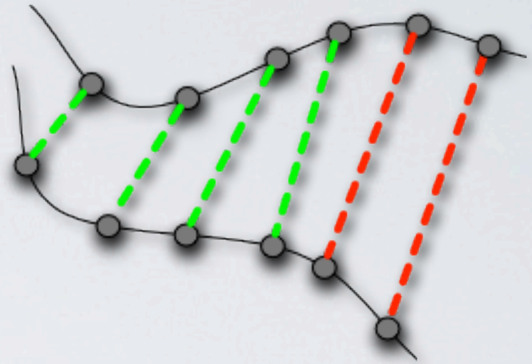
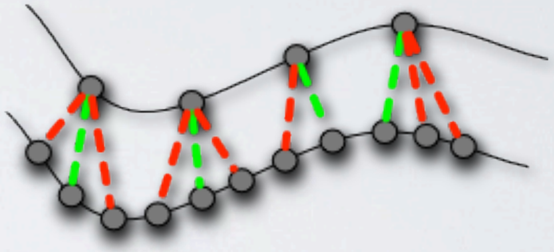
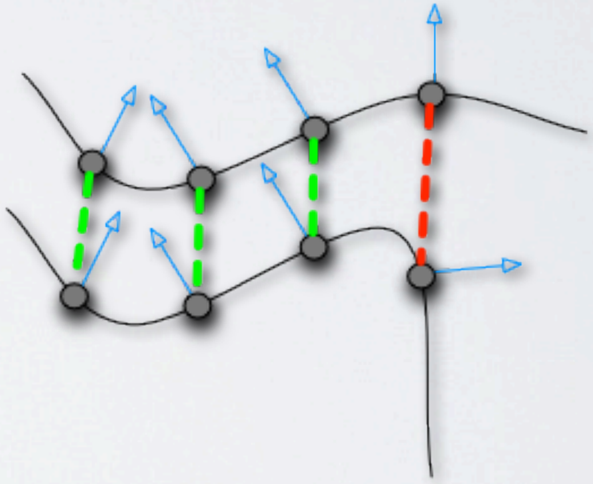
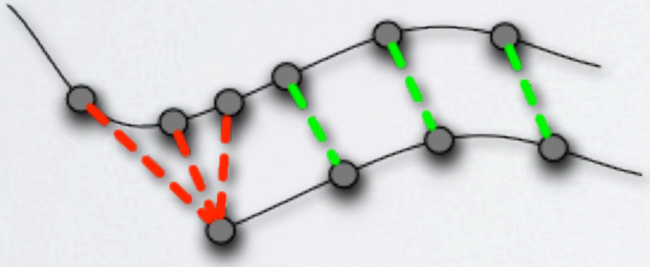
Options:

- distance
- median distance
- one to one
- sample consensus
- sample consensus 2D
- surface normal
- boundary points









Benchmarks

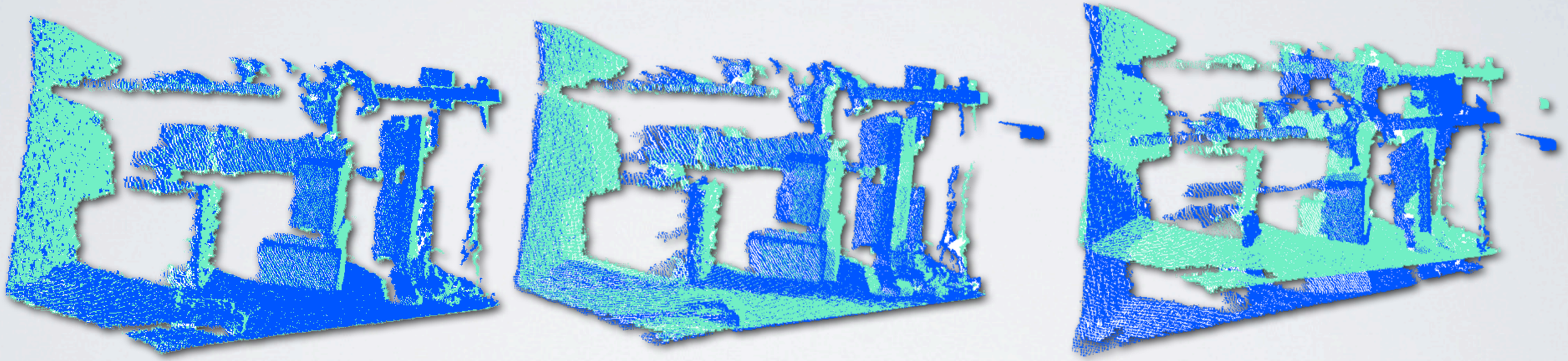
ONE	no filtering
TWO	median distance rejection (threshold = 2x median)
THREE	median distance + surface normal (threshold of 30 degrees)
FOUR	median distance + surface normal + reject correspondences that contain boundary points
FIVE	median distance + surface normal + boundary points + one to one
SIX	median distance + surface normal + boundary points + one to one + sample consensus (1000 iterations with an inlier threshold of 5 cm)

Correspondence Rejection 2/5

Benchmarks

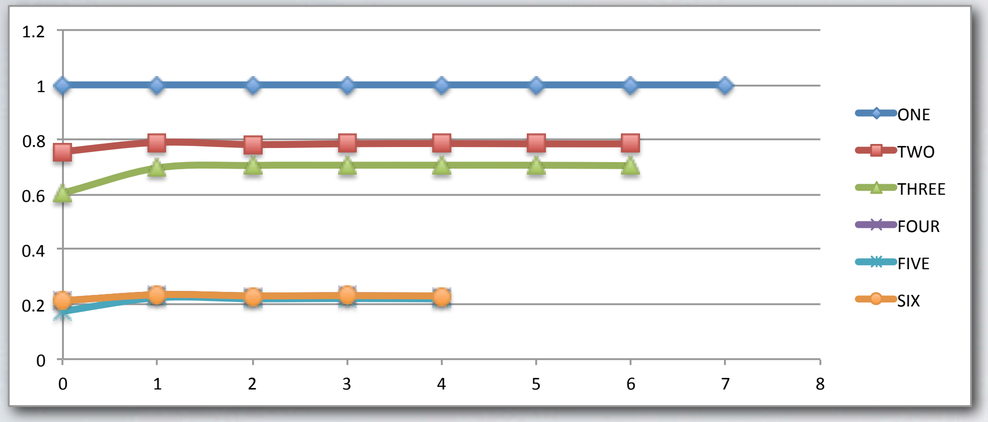
one source scan and three target scans:

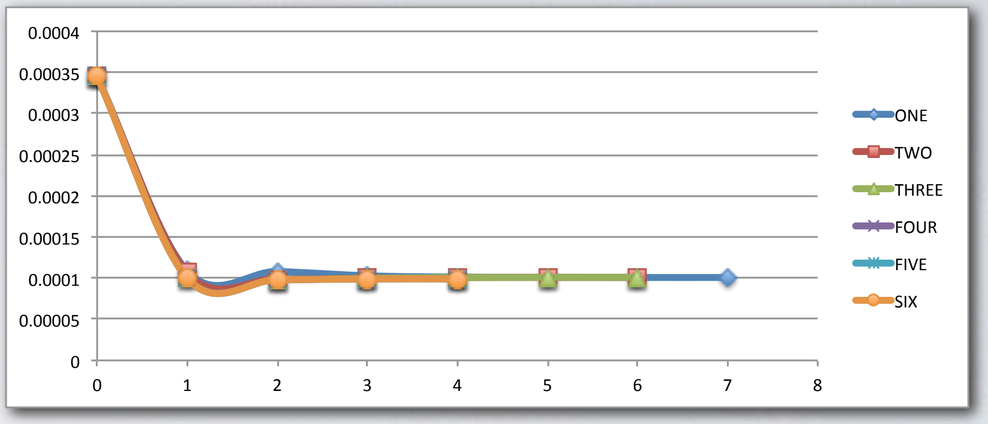
- rotation of 1.3 degrees and 1 cm translation
- rotation of 4.3 degrees and 4.5 cm translation
- rotation of 8.3 degrees and 23 cm translation



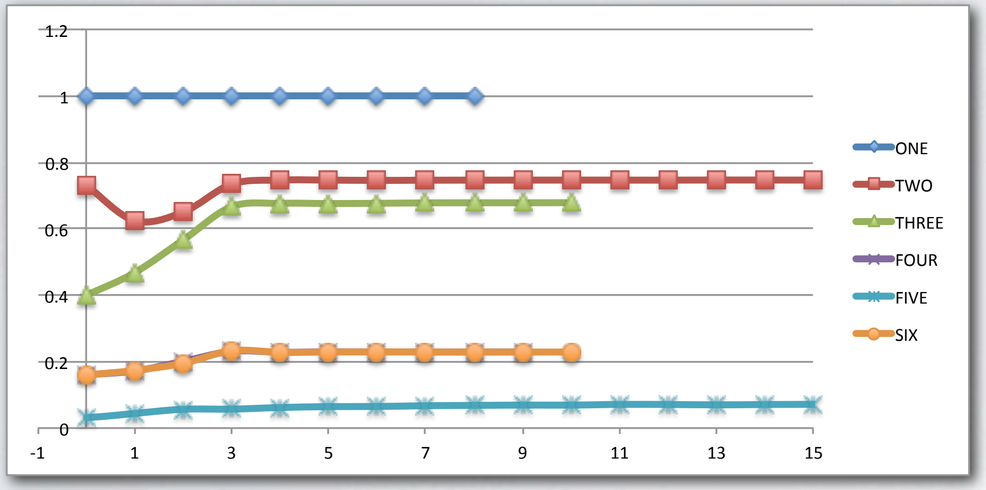
Cloud pairs

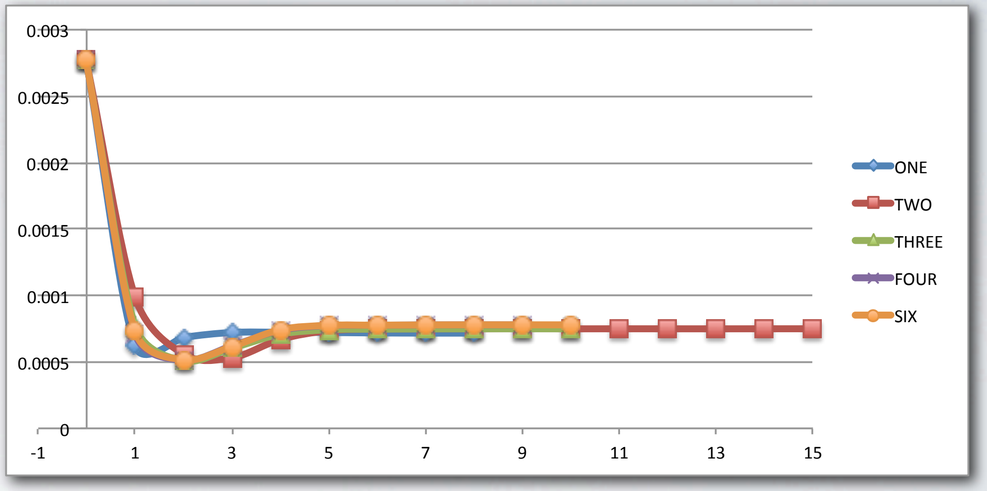
1 - 2



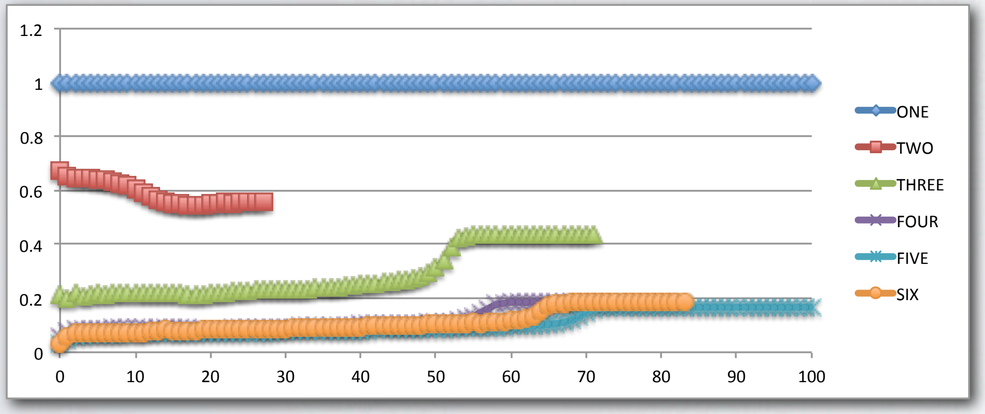


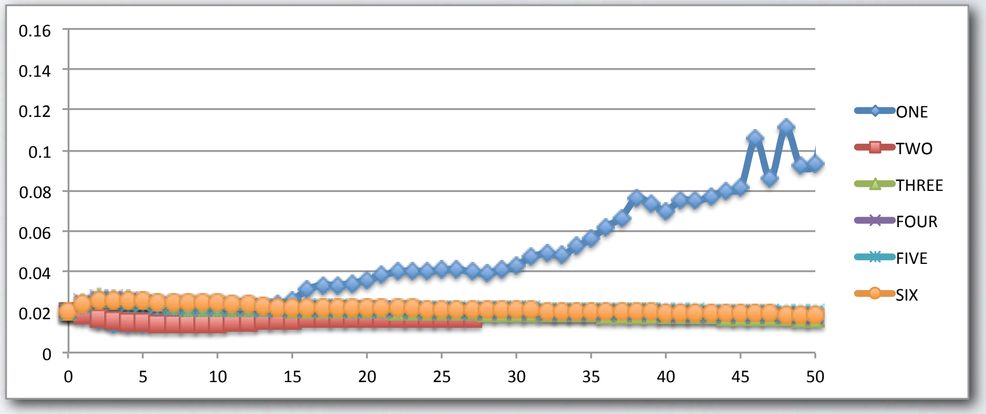
1 - 3





1 - 4

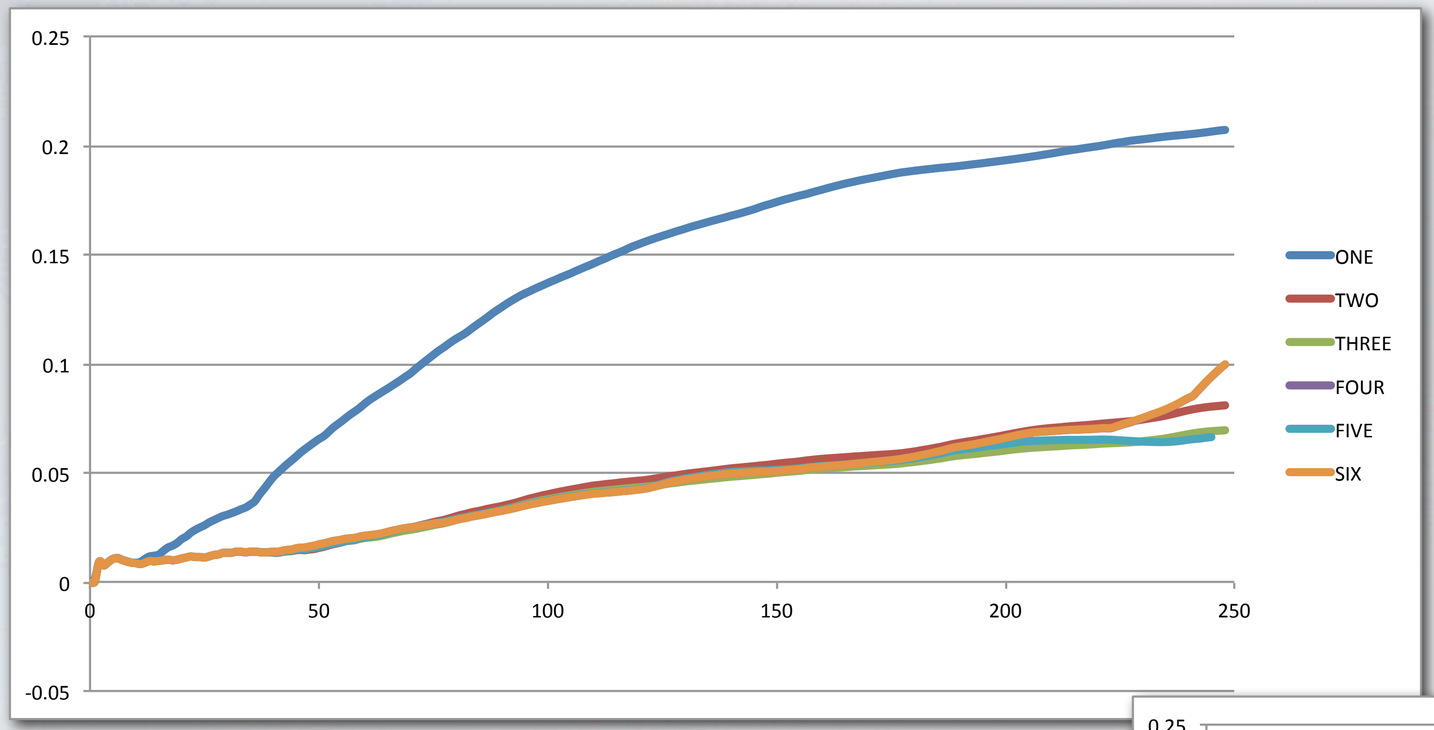




iteration vs percentage that passed filtering

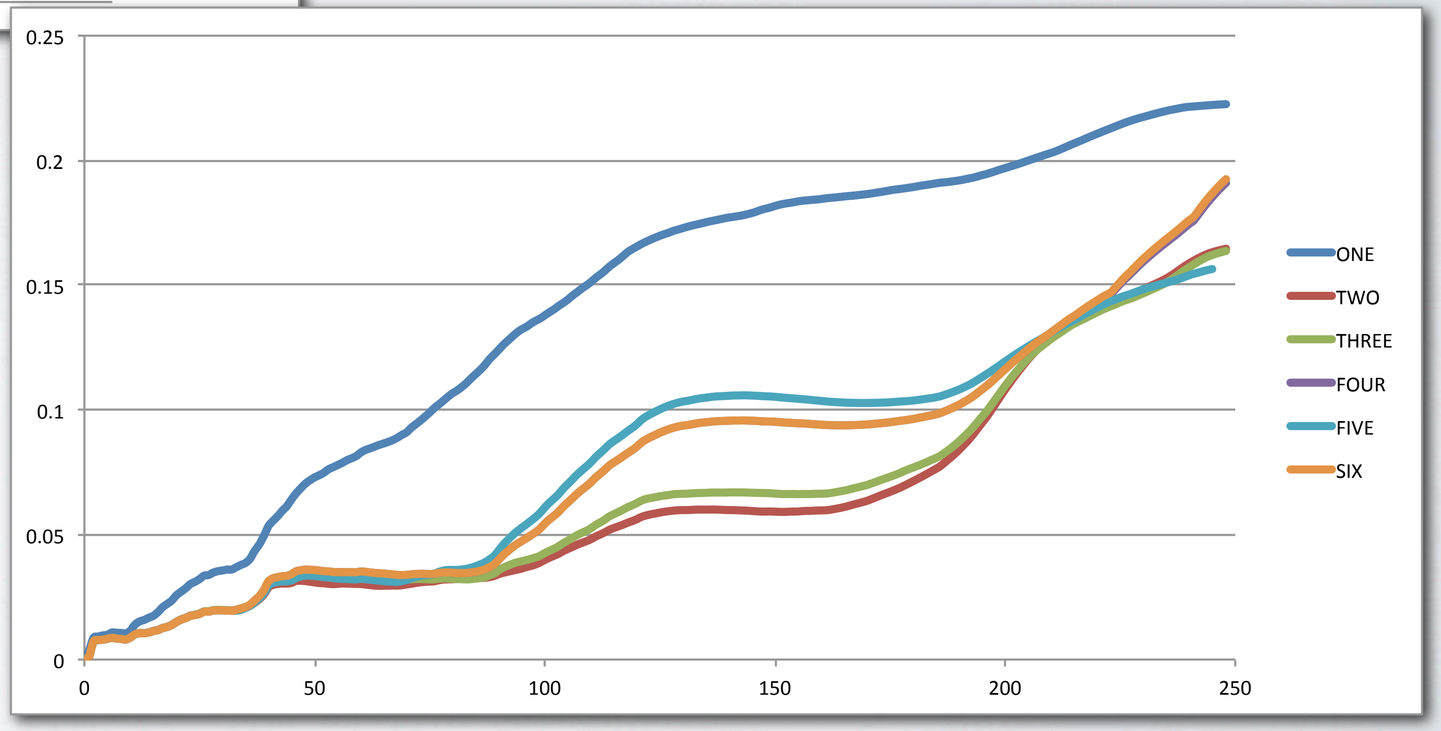
iteration vs MSE

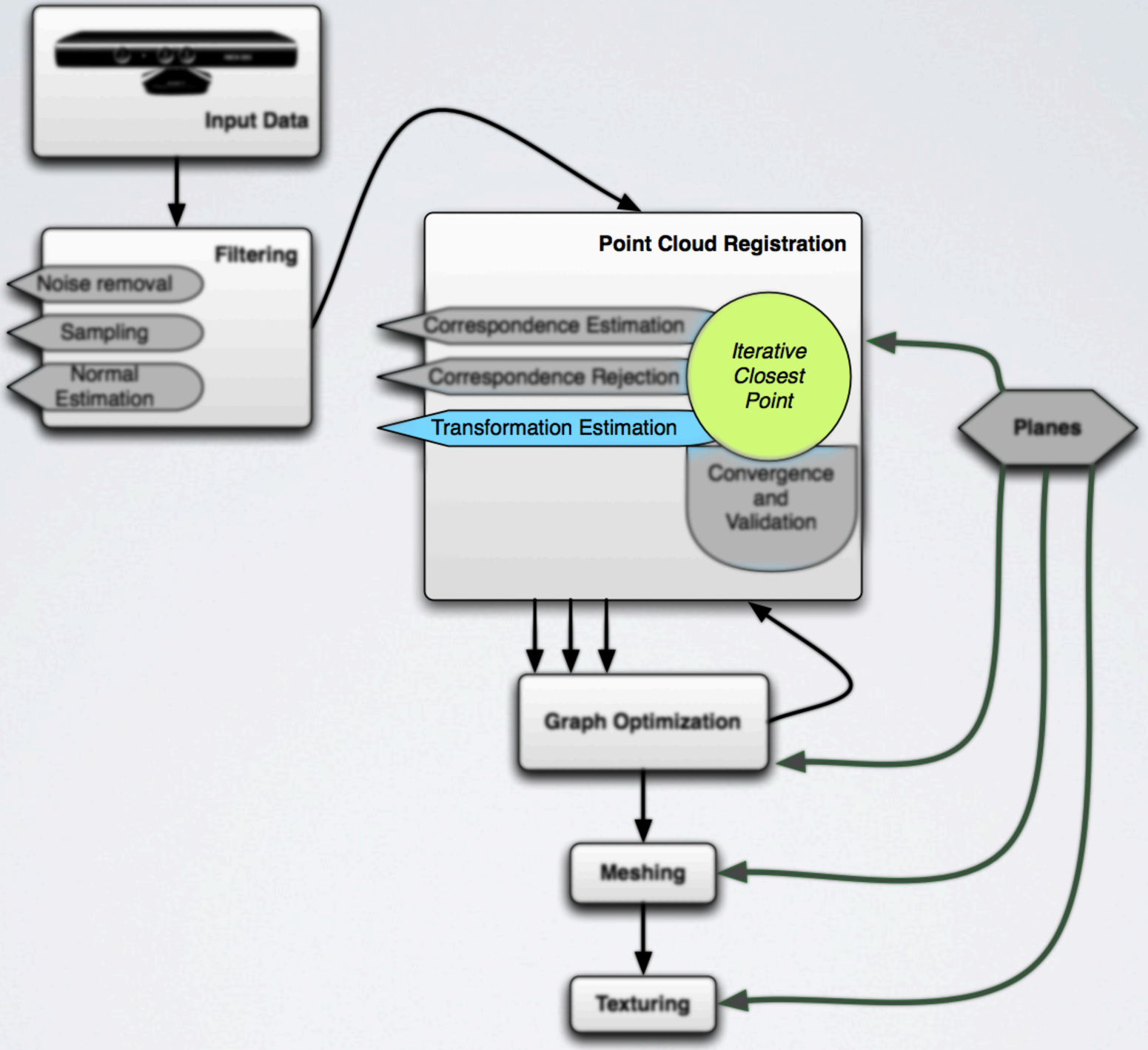
Incremental registration



cloud number vs angle RMSE

cloud number vs translation RMSE




Input Data
Filtering
Noise removal
Sampling
Normal Estimation
Point Cloud Registration
Correspondence Estimation
Correspondence Rejection
Transformation Estimation
Iterative Closest Point
Convergence and Validation
Planes
Graph Optimization
Meshing
Texturing

Error metrics:

- point to point: $\sum_{i=1}^{N} ||R\ p_i + t - q_i||^2$
- point to plane: $\sum_{i=1}^{N} ((R\ p_i + t) - q_i) \cdot n_{q_i})^2$

Methods:

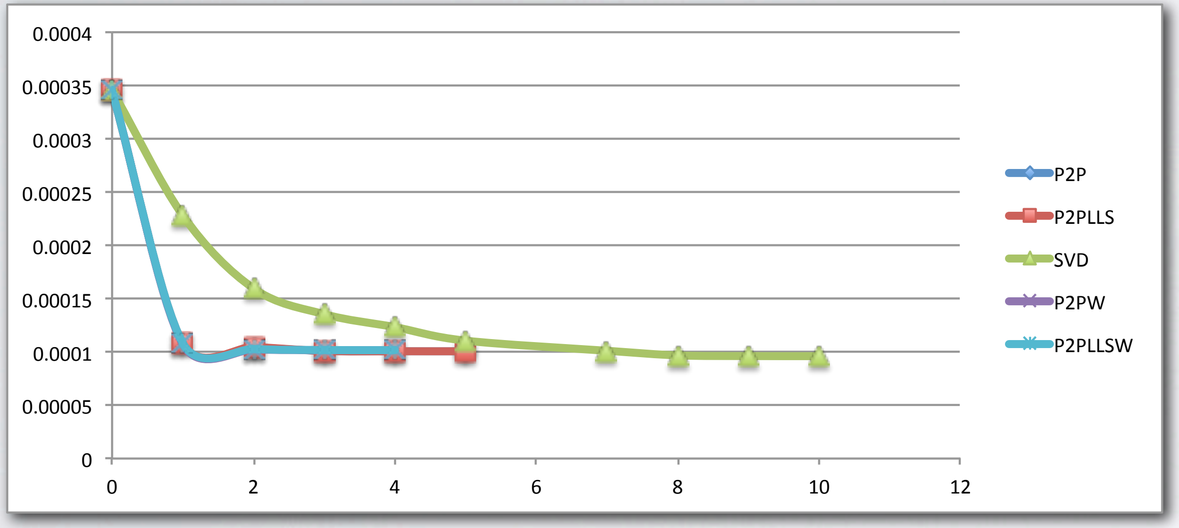
- Point to plane Linear Least Squares
- Point to plane LLS weighted
- SVD
- Point to plane LM
- Point to plane LM weighted

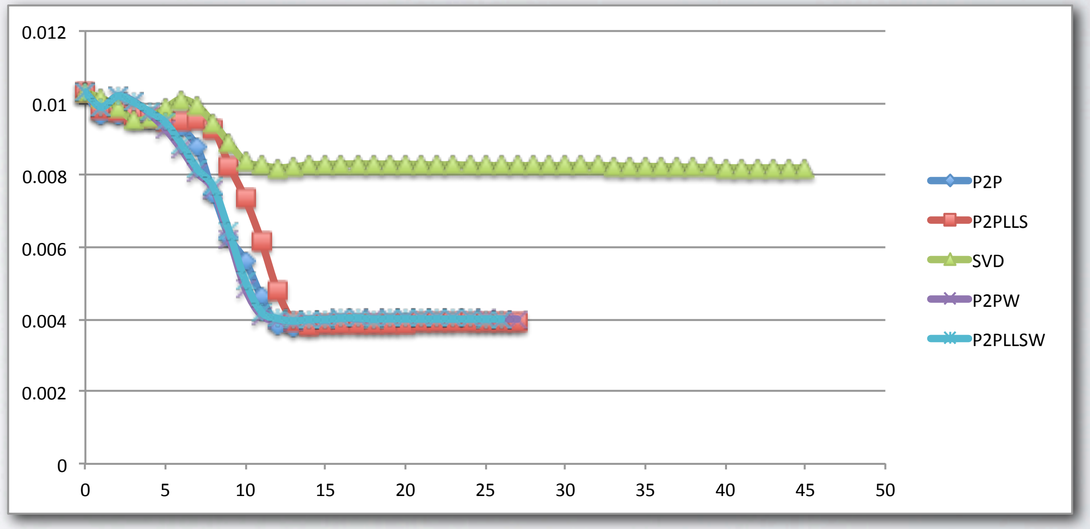
Benchmarks

Same 3 pairs of clouds

3 types of correspondences:

- noisy
- clean (filtering based on normals)
- clean + randomization

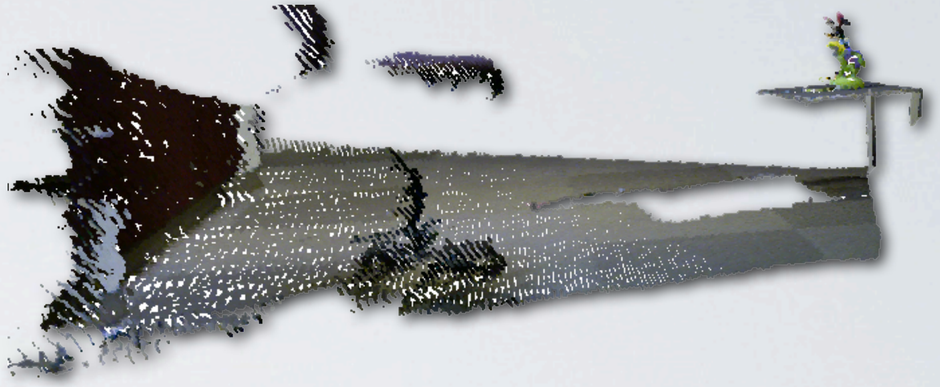




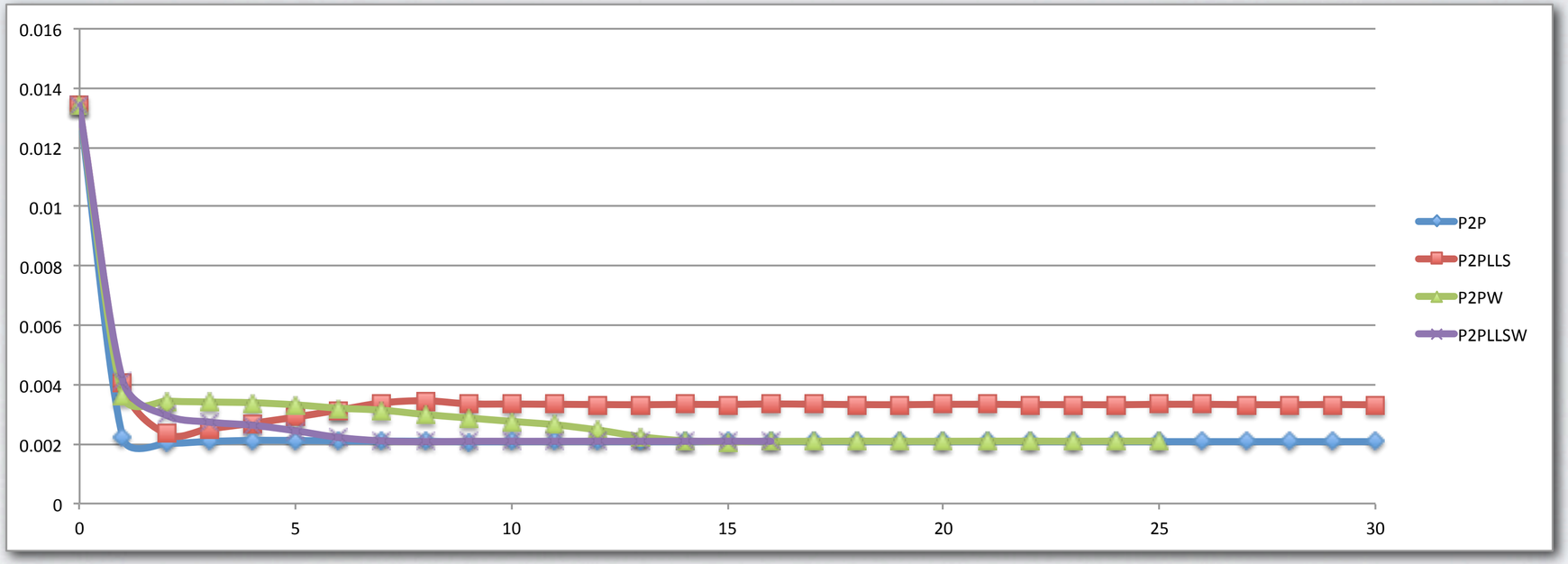
iterations vs MSE

weighting based on the camera noise model:

$$w(p_i, q_i) = 0.0012 + 0.0019 * (max(p_{i_z}, q_{i_z}) - 0.4)^2$$

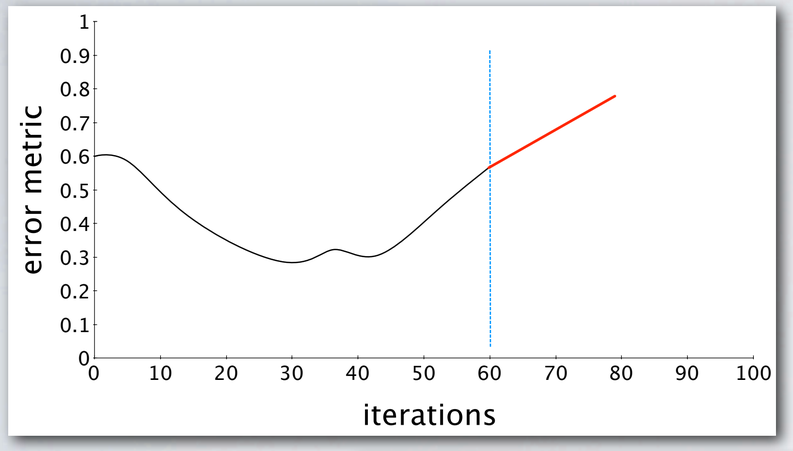


iterations vs MSE

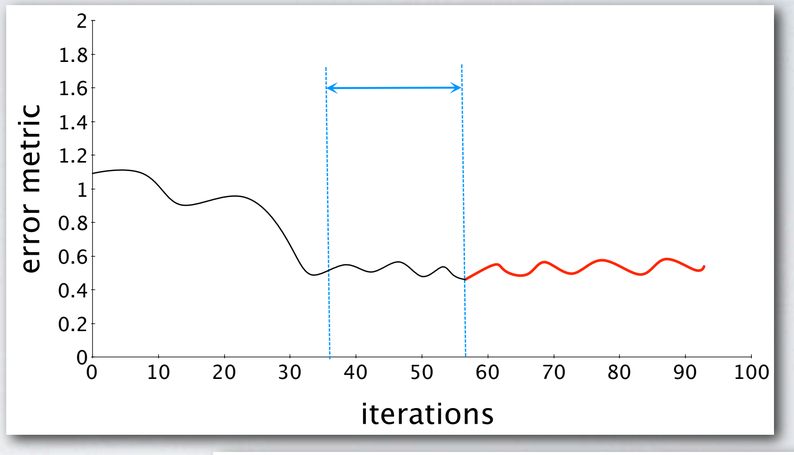


Transformation Estimation 3/3

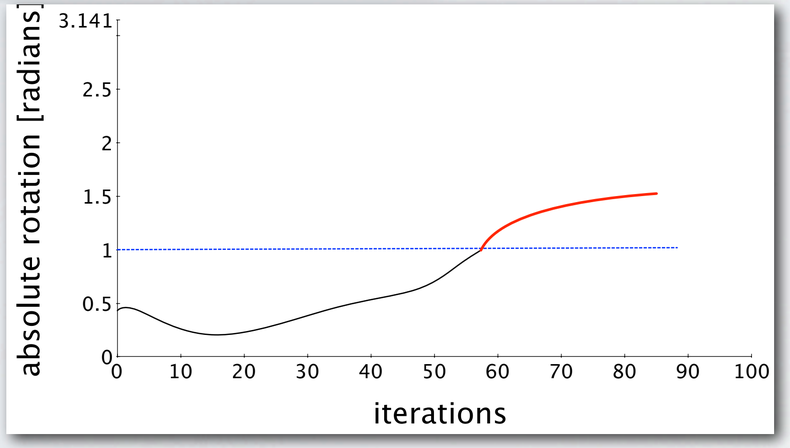
maximum number of iterations



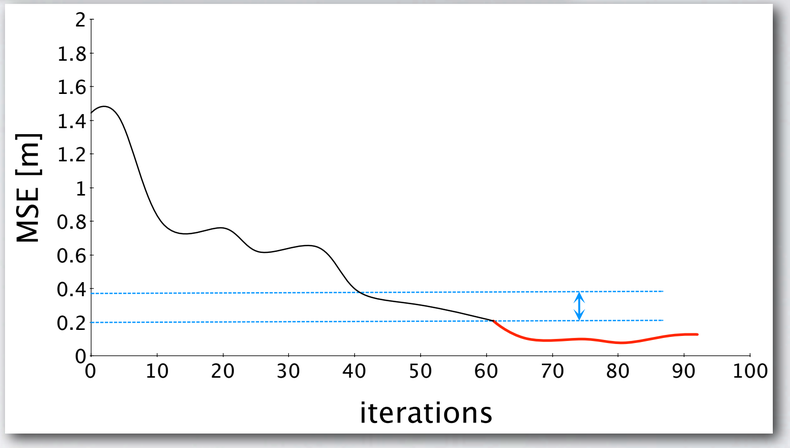
maximum number of similar iterations



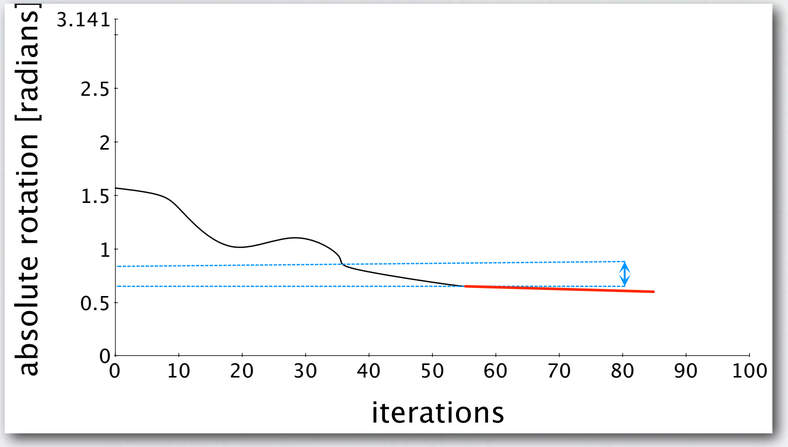
absolute transformation threshold



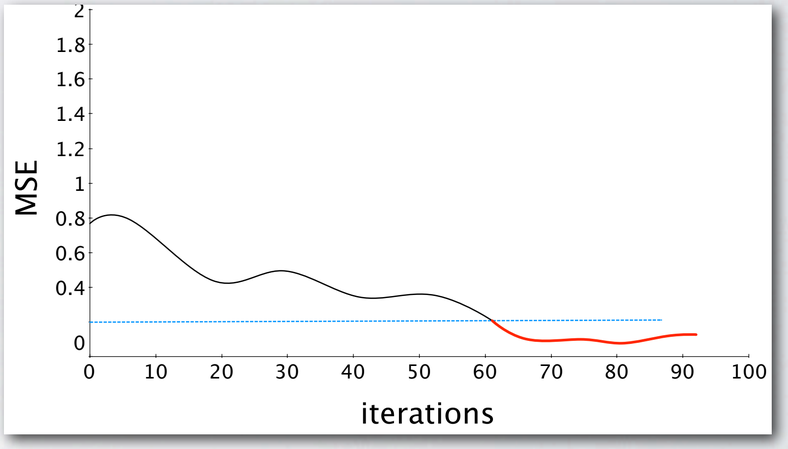
relative MSE threshold



relative transformation threshold

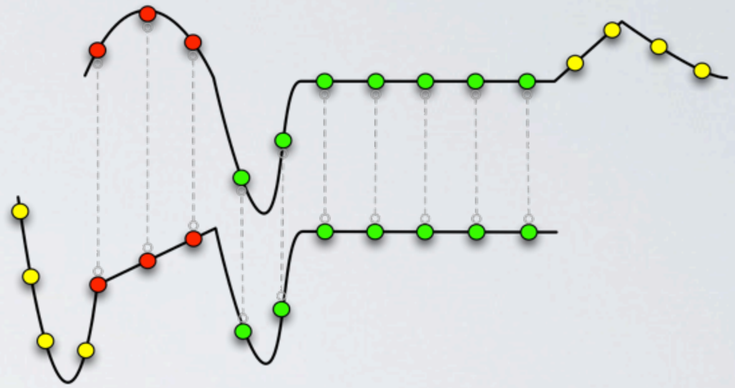


absolute MSE threshold



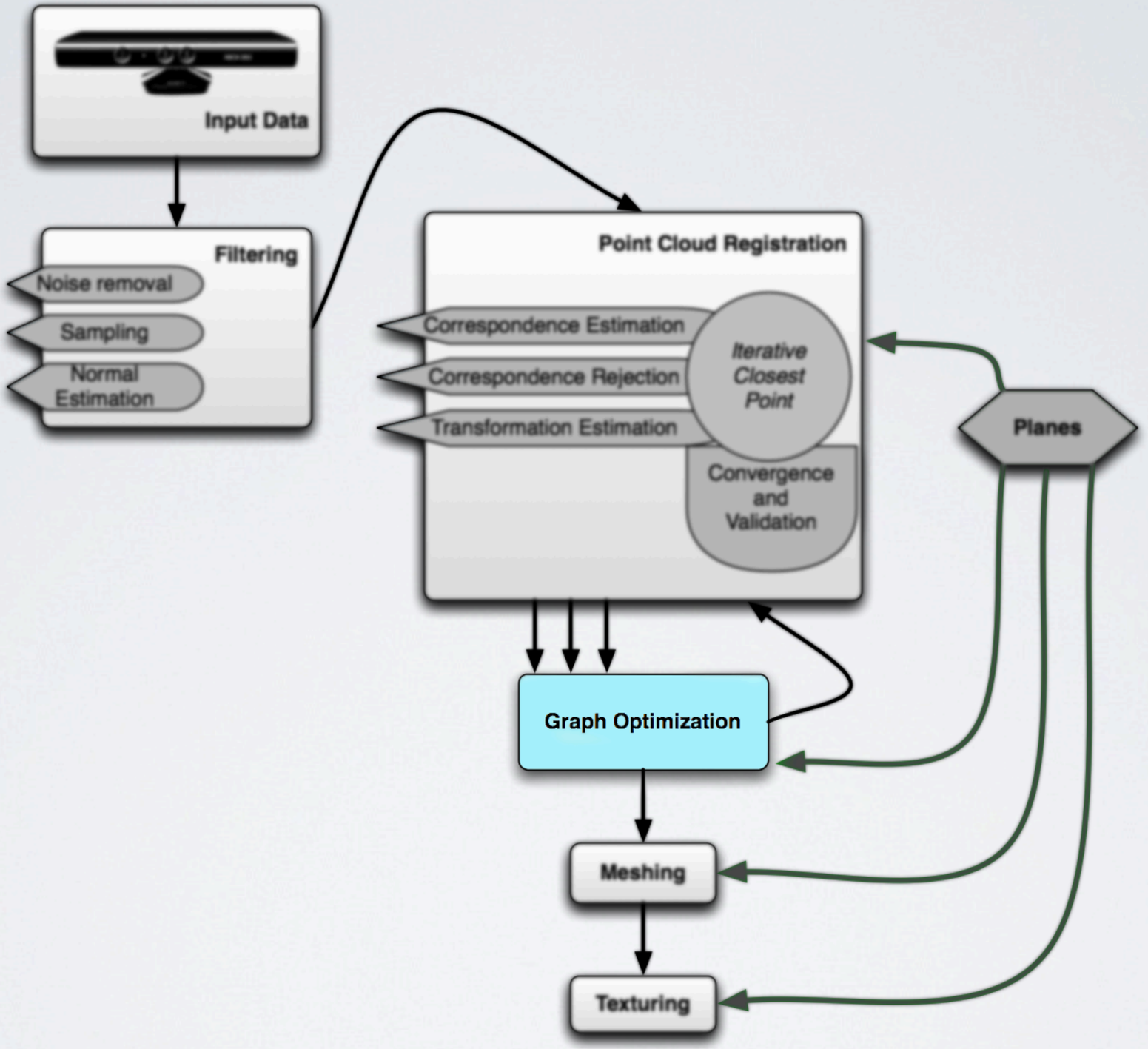
Stopping Criteria

Additional criteria for validating a transformation:



- percentage of valid dexels
- percentage of inliers
- motion limit
- stability of the overlapping regions (condition number of the inliers)

Transformation Validation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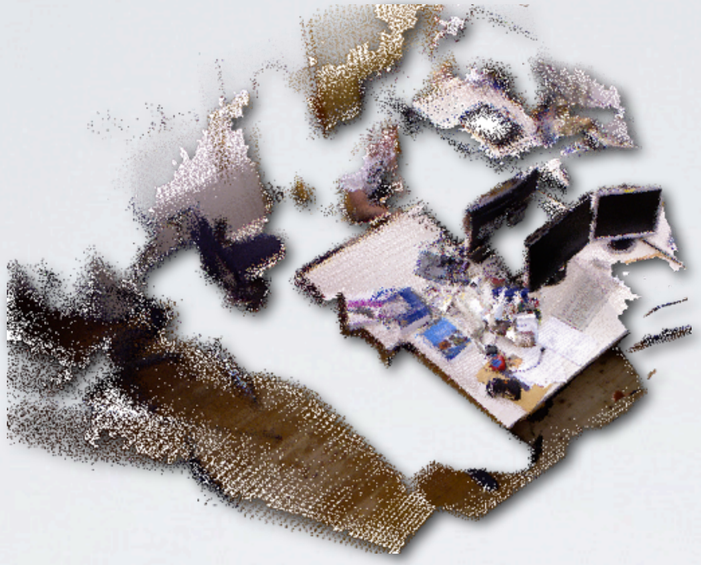
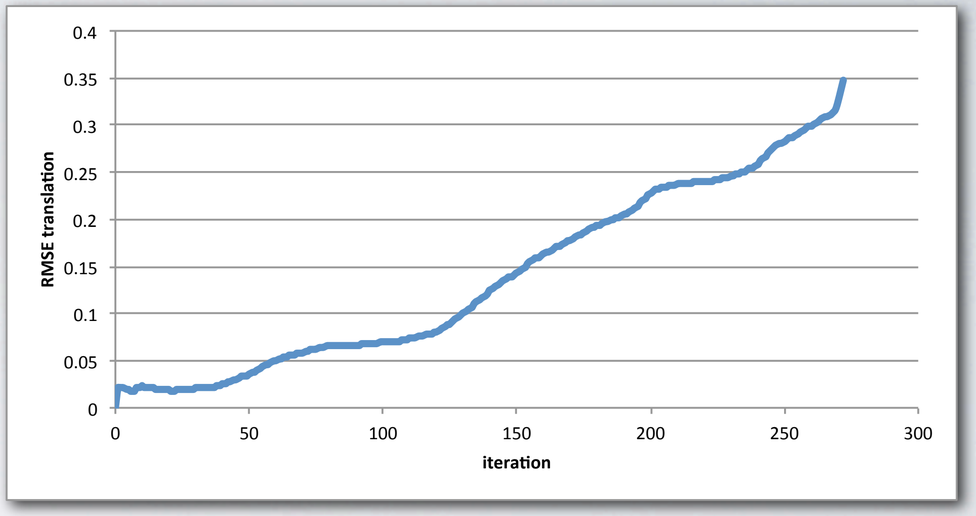
Texturing

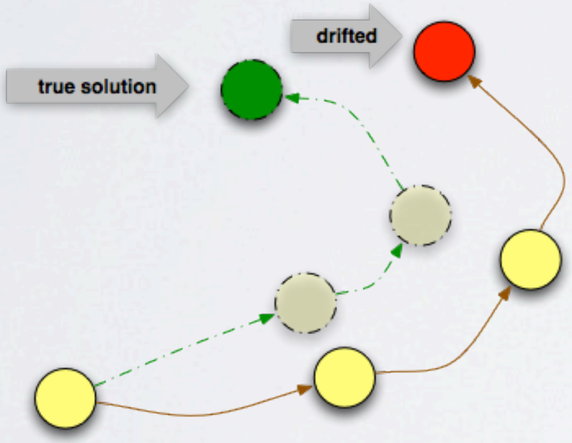
Incremental error accumulation

incremental map

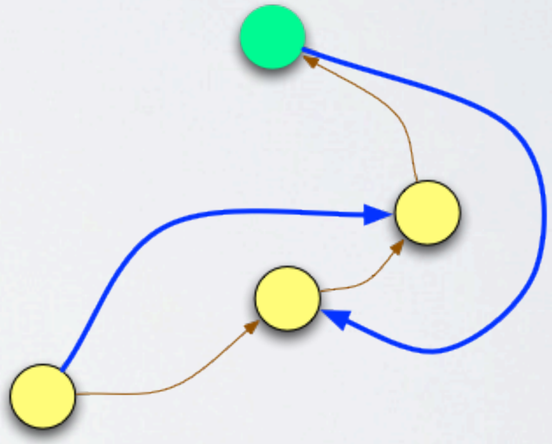


ground truth map



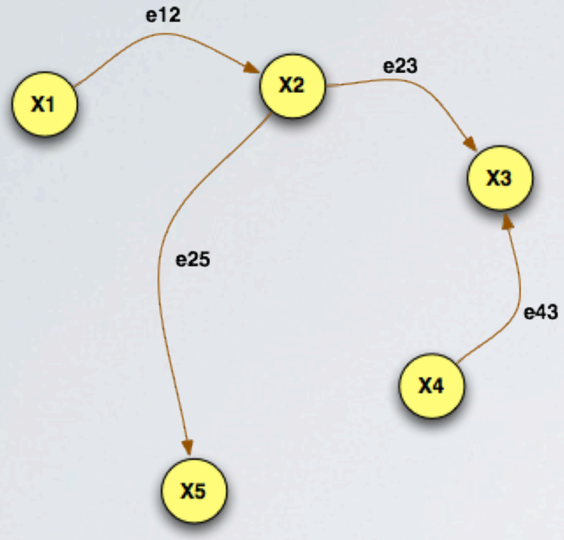


need additional links
in the graph



Graph Optimization

Graph representation



$$
\begin{aligned}
F(x) &= e_{12}^T \, \Omega_{12} \, e_{12} \\
&+ e_{23}^T \, \Omega_{23} \, e_{23} \\
&+ e_{25}^T \, \Omega_{25} \, e_{25} \\
&+ e_{43}^T \, \Omega_{43} \, e_{43}
\end{aligned}
$$

$$
\begin{aligned}
x^* &= argmin_x[F(x)] \\
F(x) &= \sum e(x_i, x_j, z_{ij})^T \Omega_{ij} e(x_i, x_j, z_{ij}) \\
e(x_i, x_j, z_{ij}) &= T(z_{ij}) T(x_i) T(x_j)^{-1}
\end{aligned}
$$

By linearization:

$$e_{ij}(\breve{x}_i + \Delta x_i, \breve{x}_j + \Delta x_j) = e_{ij}(\breve{x} + \Delta x) \simeq e_{ij} + J_{ij} \, \Delta x$$

it reduces to:

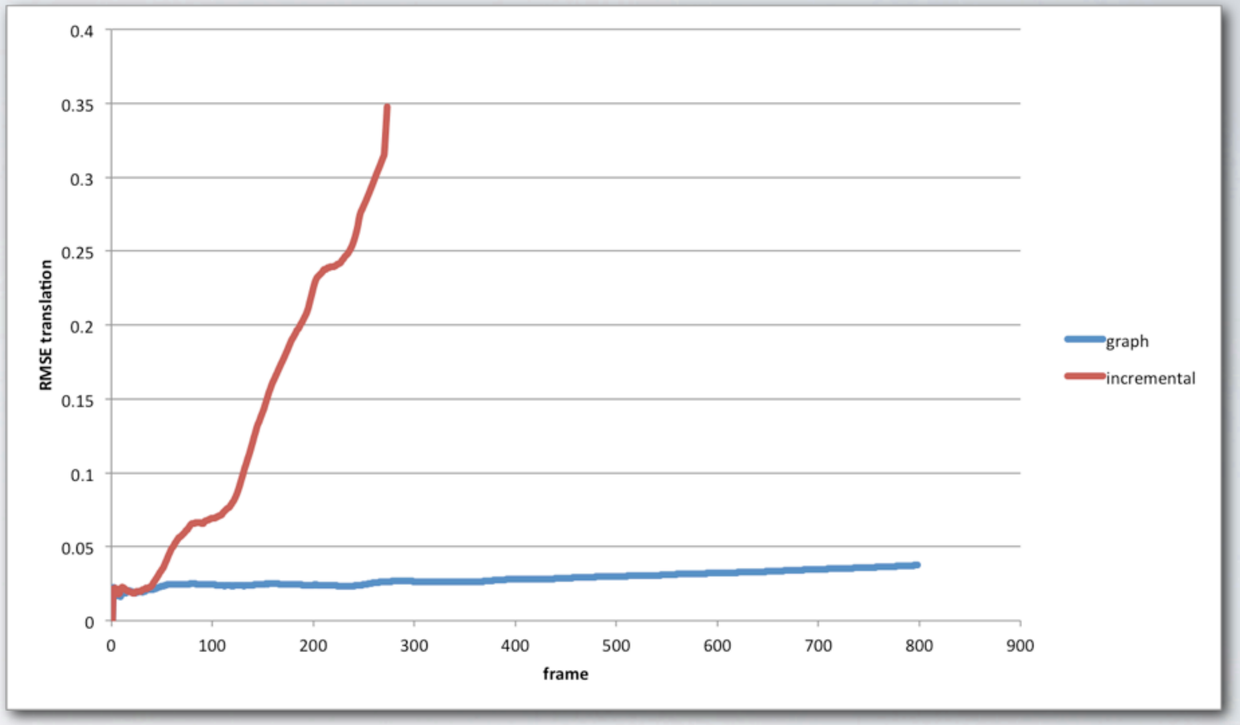
$$H \Delta x^* = -b$$

and can be solved by Gauss-Newton or Levenberg-Marquardt

Graph Optimization

Ideally: N(N-1) edges in the graph

N edges from incremental registration

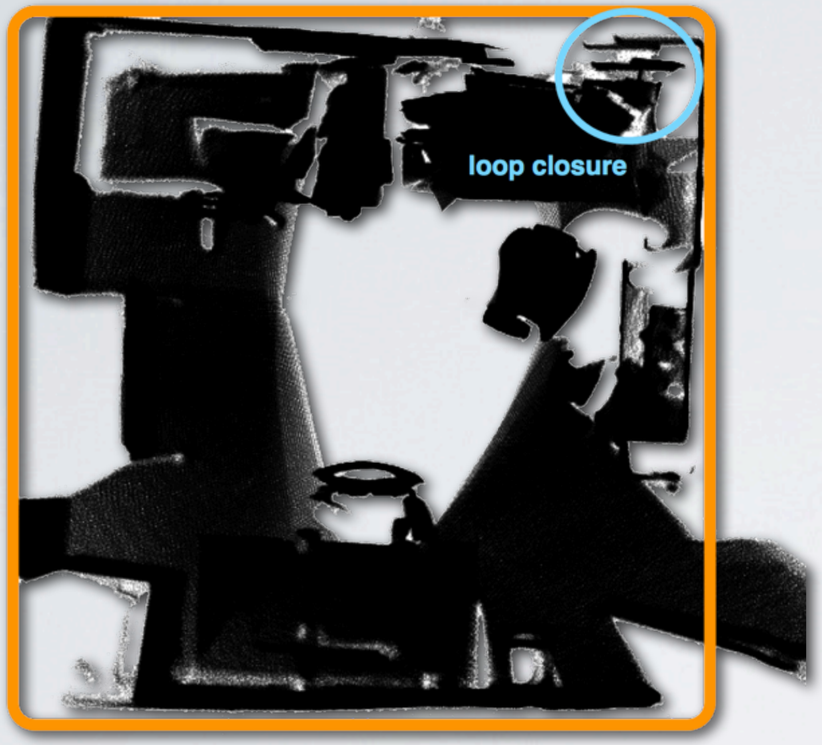


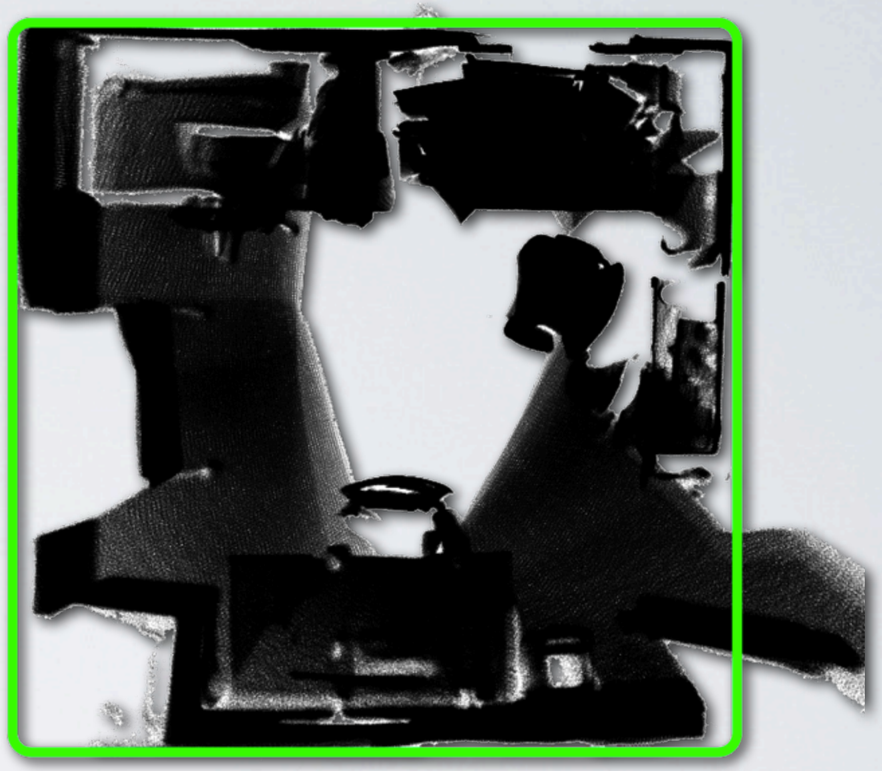
need more, how?

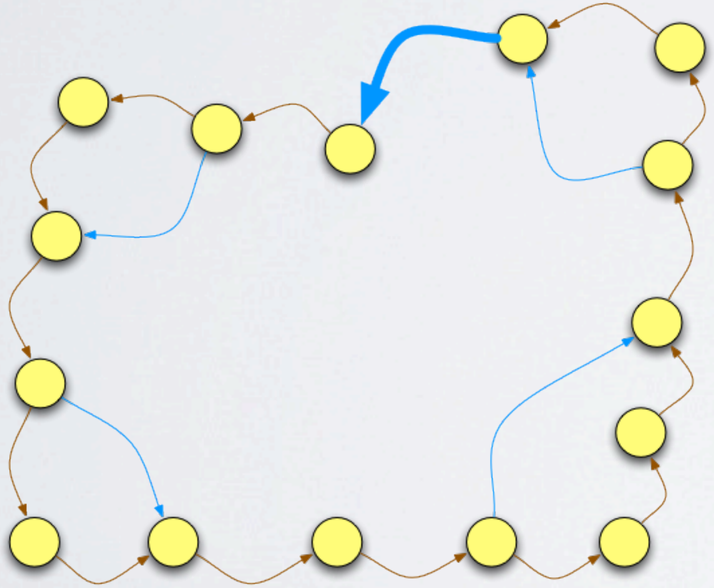
keyframes

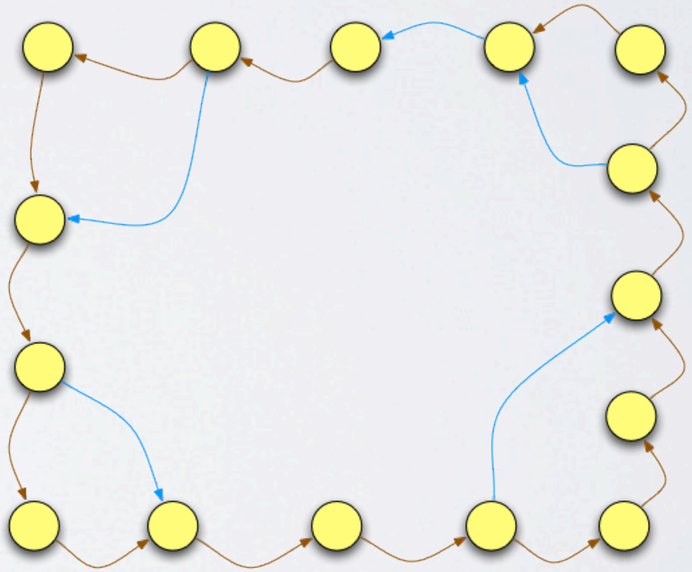
thresholding in angle, xyz and time space

Graph Optimization









Loop Closure

Edge Weights

- uniform weighting

- isotropic weighting based on the pairwise registration
  - percentage of overlap between the frames
  - condition number of the overlapping points

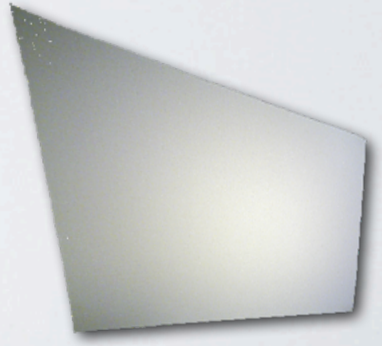
- true covariance matrix of ICP
  - by perturbation

$$\left[\frac{\delta RMSE}{\delta x}, \frac{\delta RMSE}{\delta y}, \frac{\delta RMSE}{\delta z}, \frac{\delta RMSE}{\delta \alpha}, \frac{\delta RMSE}{\delta \beta}, \frac{\delta RMSE}{\delta \gamma}\right] \qquad C = J\,J^T$$

  - covariance as the cloud stability (Gelfand et al.)
  - ICP covariance in closed form (Censi et al.)

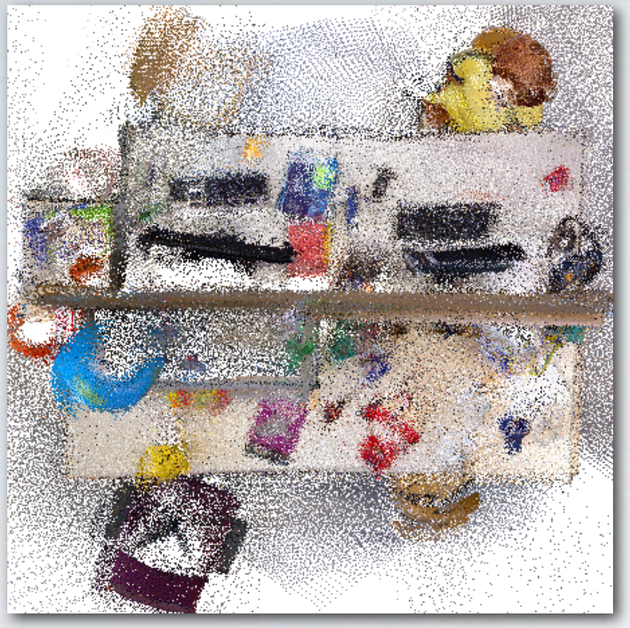
Split the graph when edges are not good enough

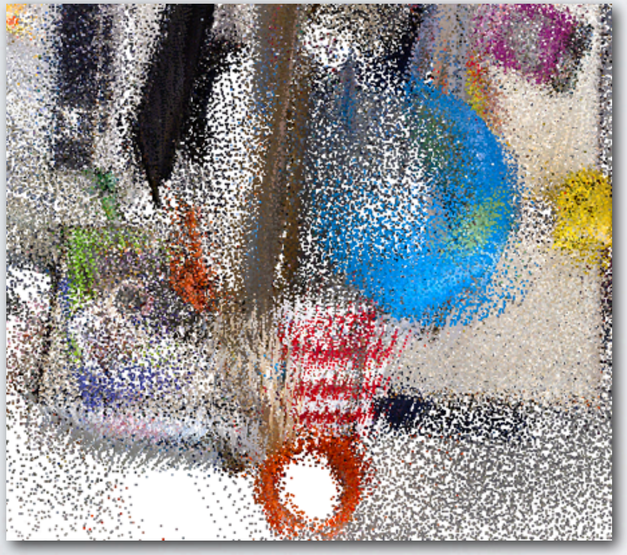
culprit frames



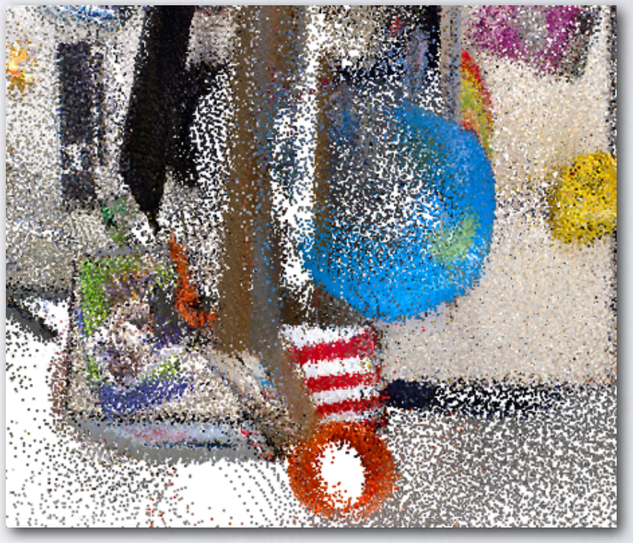
Graph Optimization 2/2

$$argmin_{R_i,t_i}\Big(\sum_{clouds\ i}\sum_{clouds\ j}\sum_{points\ k}\sum_{points\ l}[[(R_i\,p_{i,k}+t_i)-(R_j\,p_{j,l}+t_j)]\cdot(R_j\,n_{j,l})\,w_{i,j,k,l}]^2\Big)$$

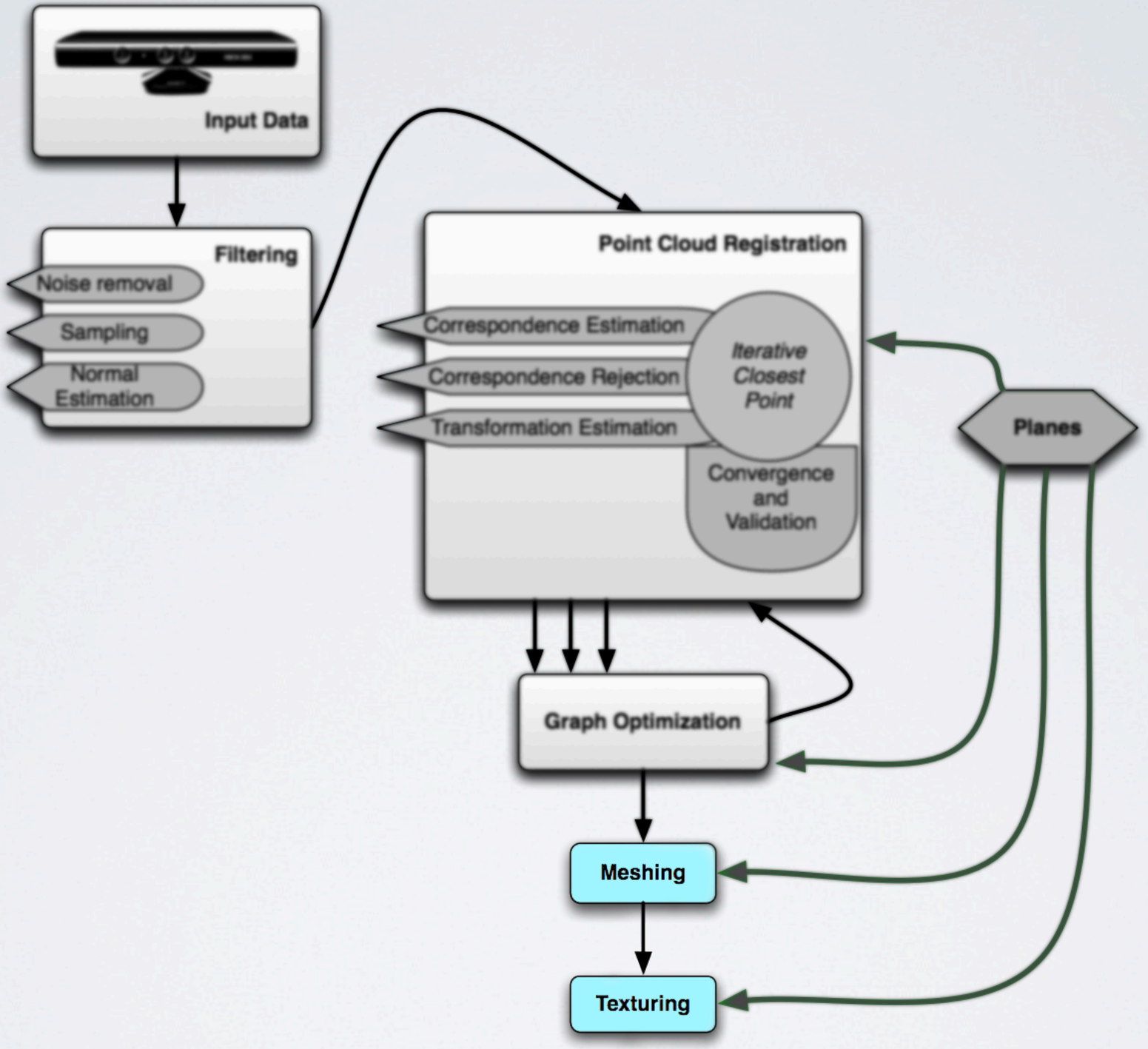




Dataset	Pose graph		Global ICP	
	Angular RMSE [degrees]	Translation RMSE [m]	Angular RMSE [degrees]	Translation RMSE [m]
freiburg1_360	12.93	0.337	9.76	0.201
freiburg1_desk	3.08	0.071	2.77	0.052
freiburg1_desk2	4.25	0.141	3.46	0.161
freiburg1_rpy	3.41	0.081	3.86	0.123
freiburg1_xyz	1.62	0.033	1.52	0.032
freiburg3_long_office_household	4.53	0.098	4.25	0.068



Global ICP


Input Data
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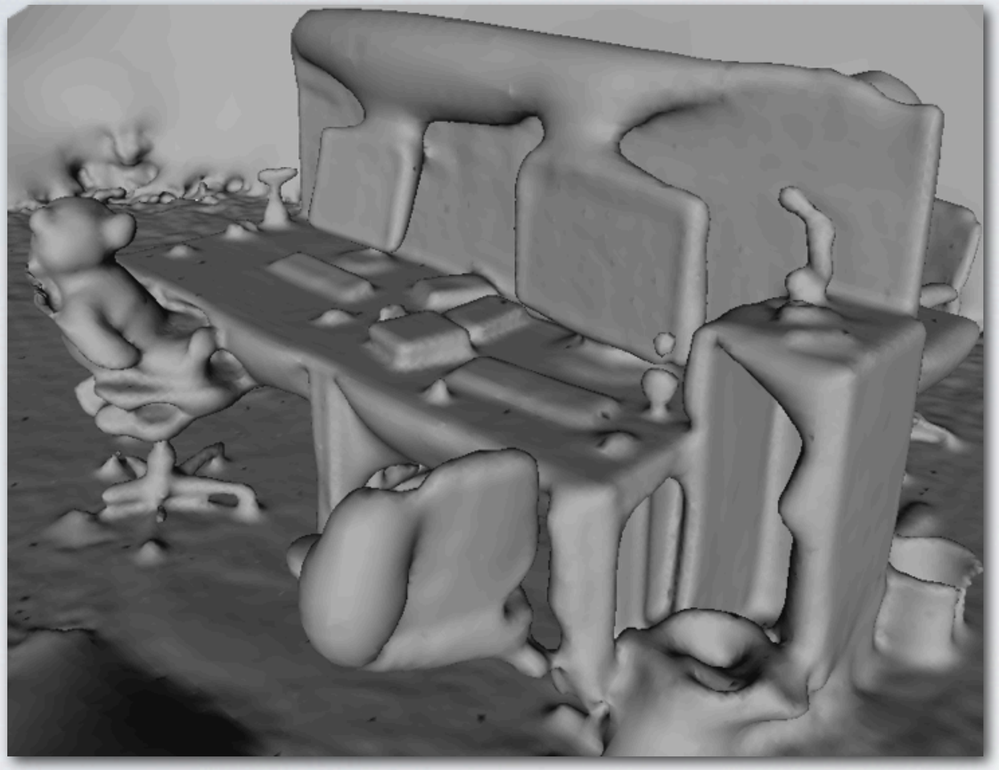
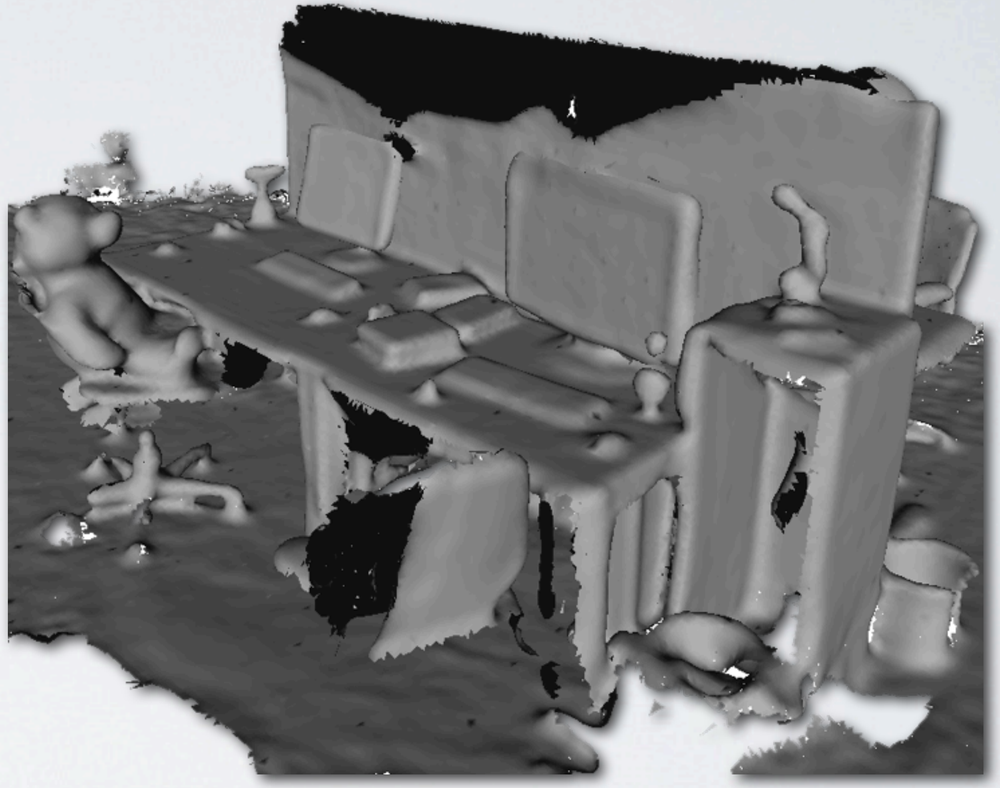
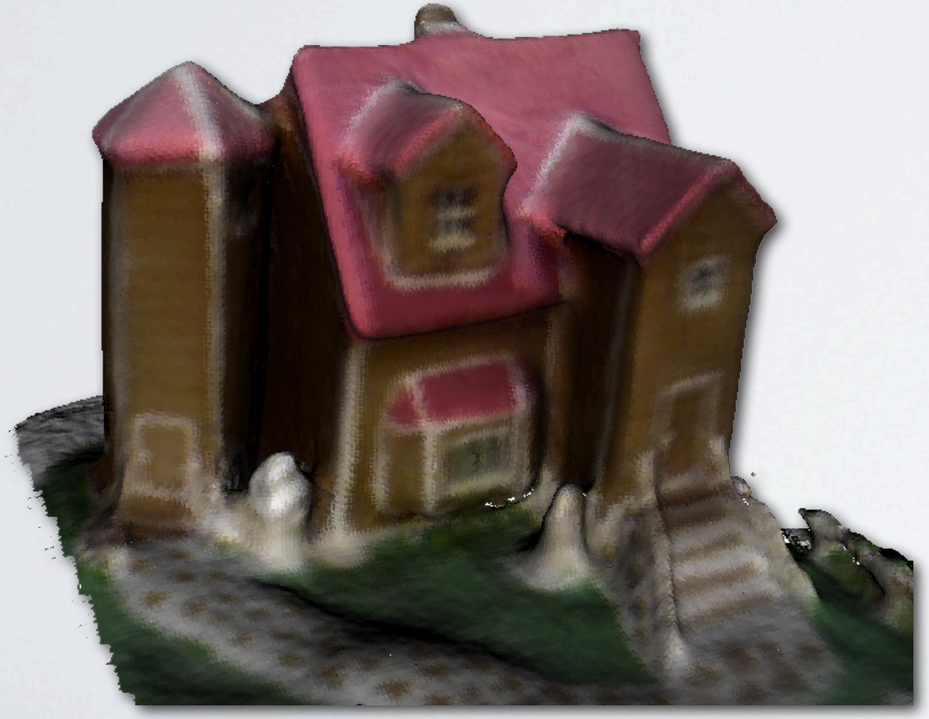


Poisson meshing with hallucinations



cleaned up

transfer color



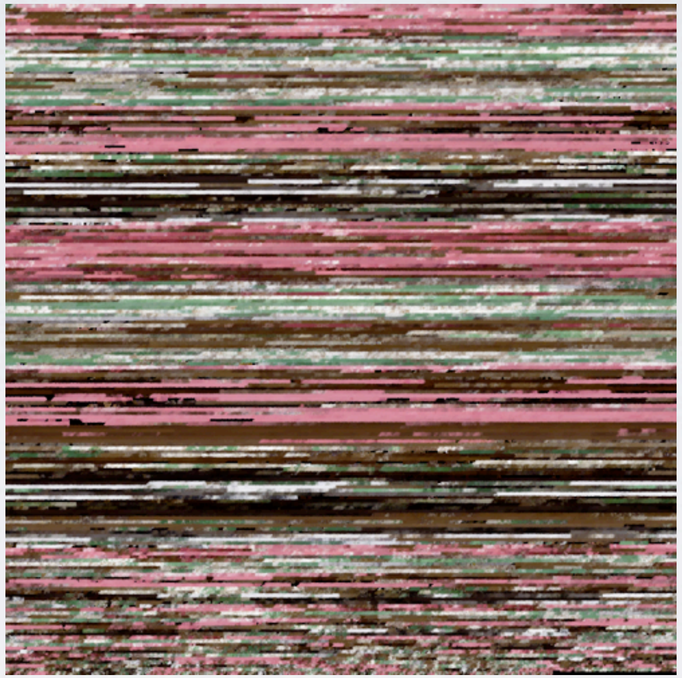
Vertex coloring

bad with compressed meshes

Meshing and Texturing

UV Mapping

trivial per-triangle



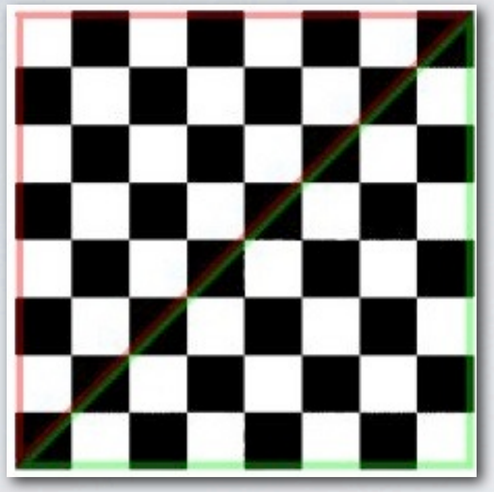
space-optimizing
trivial per-triangle

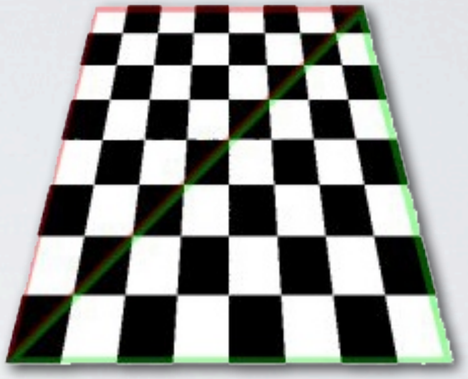
Maya automatic
UV mapping

UV Mapping

Color bleeding between triangles from different parts of the mesh

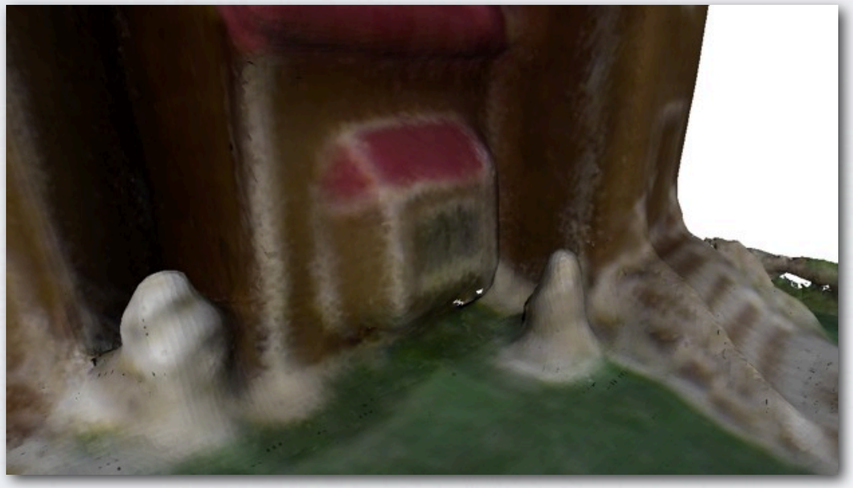
Need the texture to preserve the triangle neighborhoods!





affine transformation

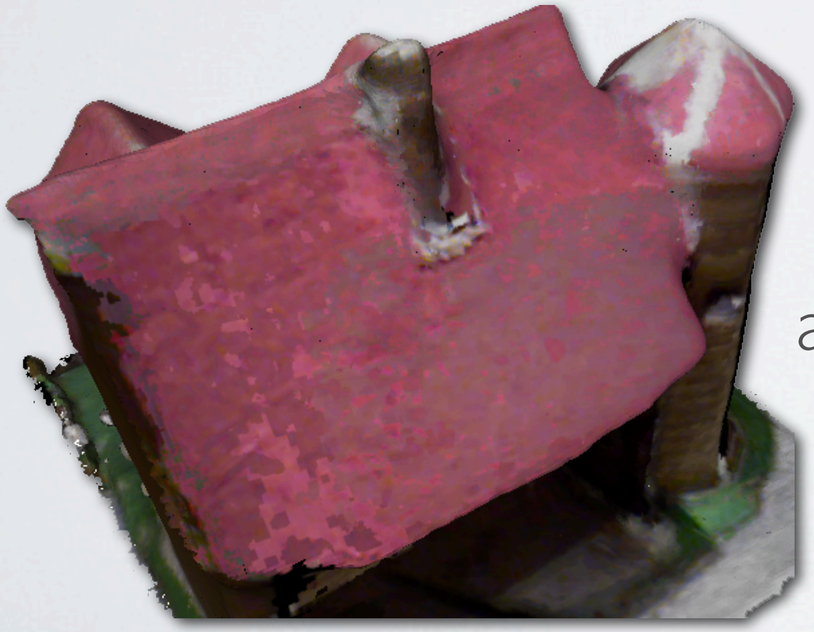
perspective transformation



Meshing and Texturing

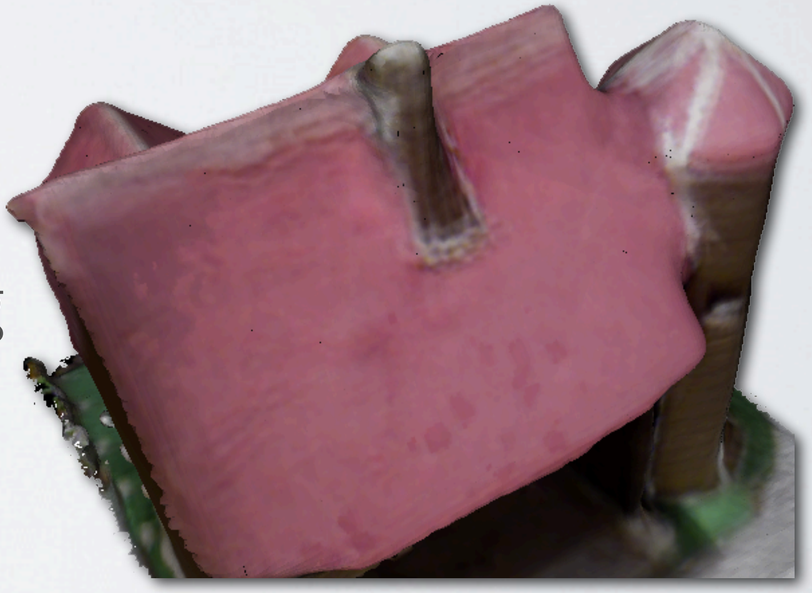
Weighting texel contributions:

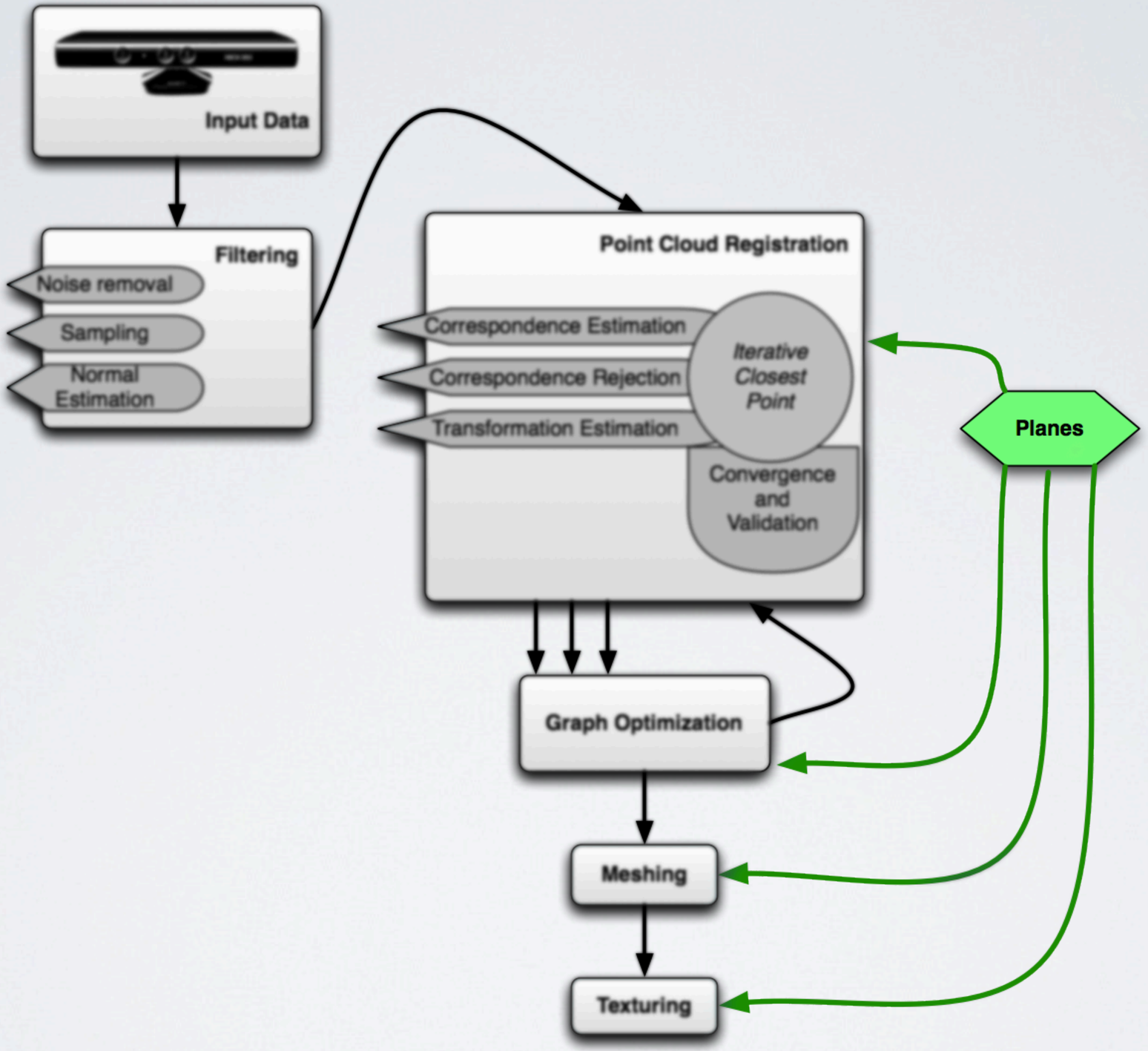
- angle between the surface normal and the viewing direction of the camera
- distance of the 3D point on the mesh triangle to the camera center
- linear combination of the previous two
- pixel area of the mesh triangle in the camera image



no averaging

with averaging

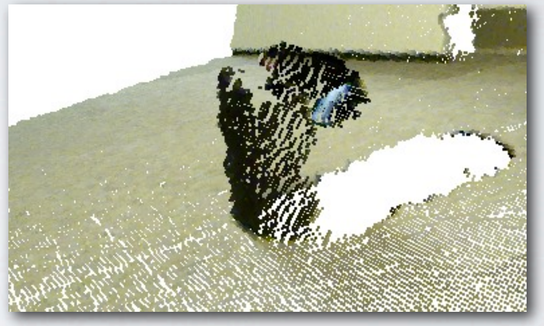


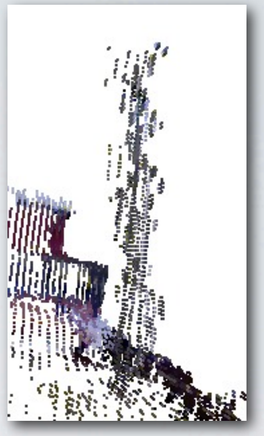

Input Data
Filtering
Noise removal
Sampling
Normal Estimation
Point Cloud Registration
Correspondence Estimation
Correspondence Rejection
Transformation Estimation
Iterative Closest Point
Convergence and Validation
Planes
Graph Optimization
Meshing
Texturing

Geometric Features

- PFH, SHOT, FPFH, NARF, spin images etc.
- semantic mapping concepts:
  - cylinders
  - spheres
  - planes

very frequent in indoor mapping

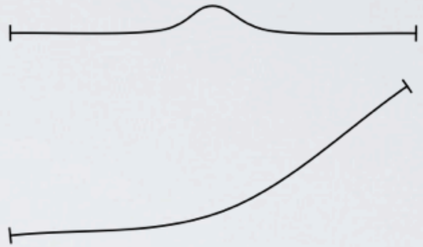




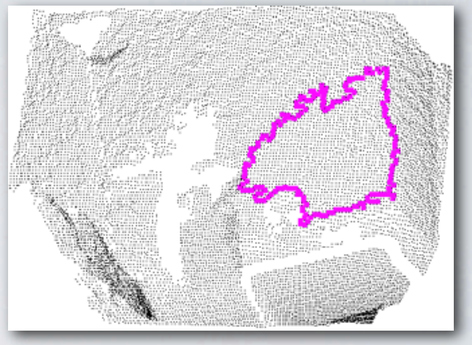
Planes

Plane Extraction

1. Region growing



seed points + use normal, curvature, Euclidean distance to grow planar regions



2. Based on RANSAC

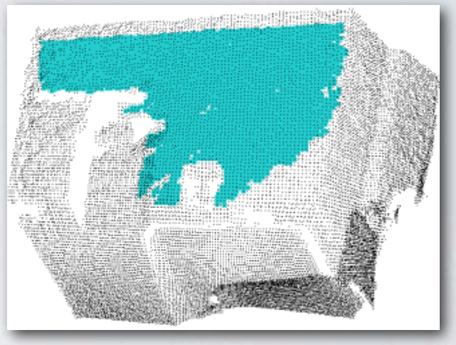
RANSAC to find plane inliers

clustering

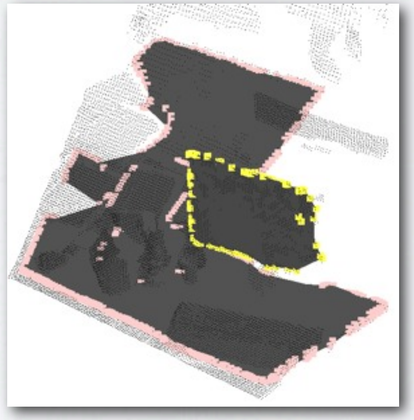
refine plane parameters and inliers iteratively using PCA

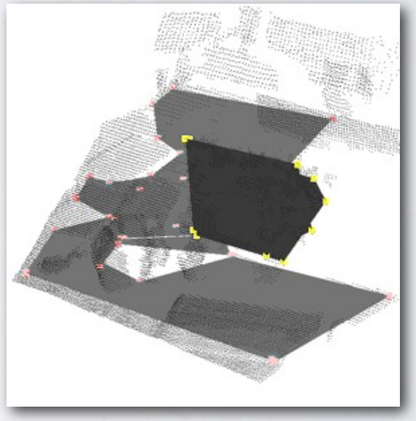
concave hull of the points

simplify the contour



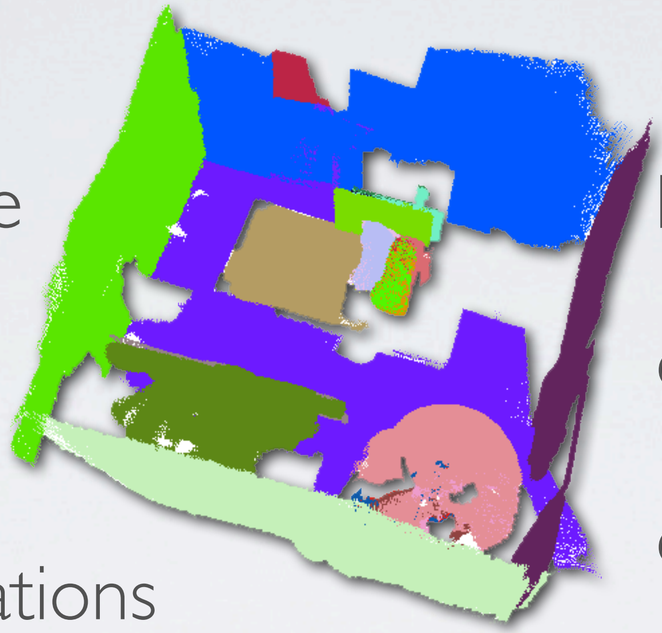
Planes





Plane Tracking

1. frame to frame
   - project inliers from one image to the other
   - threshold
2. frame to plane map
   - get candidates via equations
   - project source plane contour into target plane
   - compute intersection area
   - threshold



Plane Fusion

- weighted average of the plane parameters
- project source plane contour to target plane
- compute union of the contour polygons
- simplify the polygon

Planes

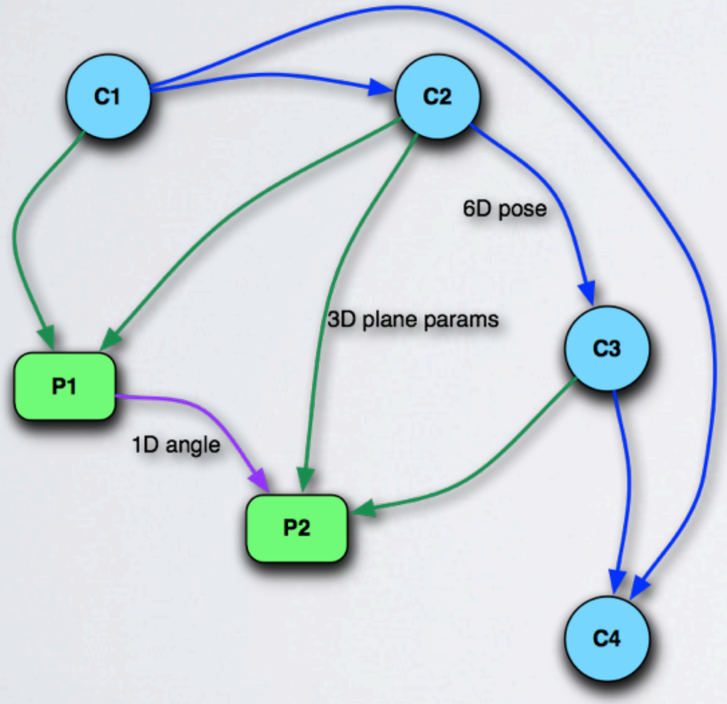
Planes as landmarks in the graph

$$e = \begin{bmatrix} R^T * \vec{n} \\ \vec{n} \circ t + d \end{bmatrix} - \begin{bmatrix} \vec{n}_m \\ d_m \end{bmatrix}$$

Observation edge - camera node to plane node

$$e = \vec{n_{src}}^T \vec{n_{tgt}} - \alpha$$

Manhattan edge - plane node to plane node

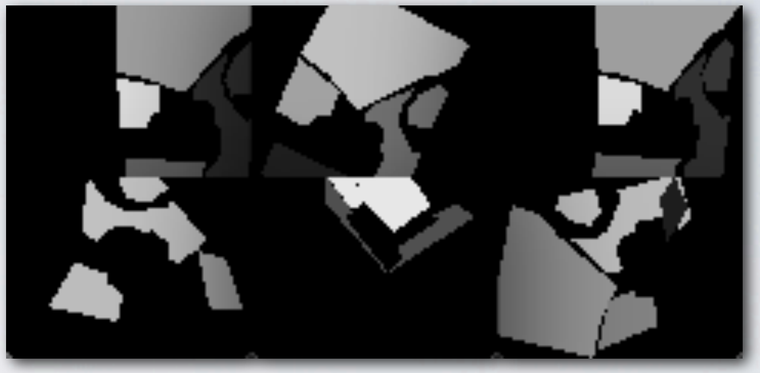


Before

After

Planes

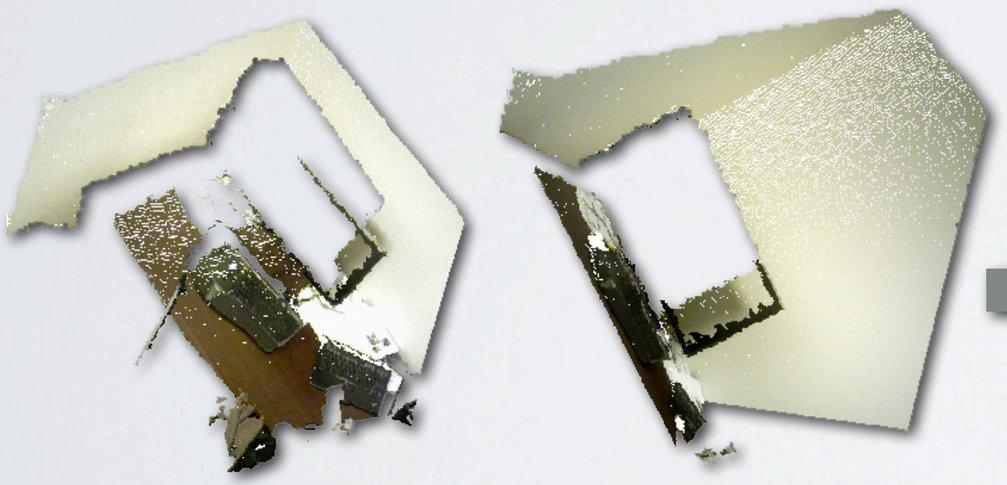
Frame to frame alignment using planes



1. RANSAC and rendered depth maps

    1. choose first & second pairs at random
    2. check if the angle difference between the normals of the first pair is close to that of the second pair - if not, goto 1.
    3. choose third pair at random
    4. check if all the angles are consistent
    5. compute the transformation T using the 3 plane pairs
    6. render the source planes transformed by T
    7. compute the number of inliers between the rendered source and target maps
    8. if inliers > max, store the current transformation

Planes



good

fail

Planes

Frame to frame alignment using planes

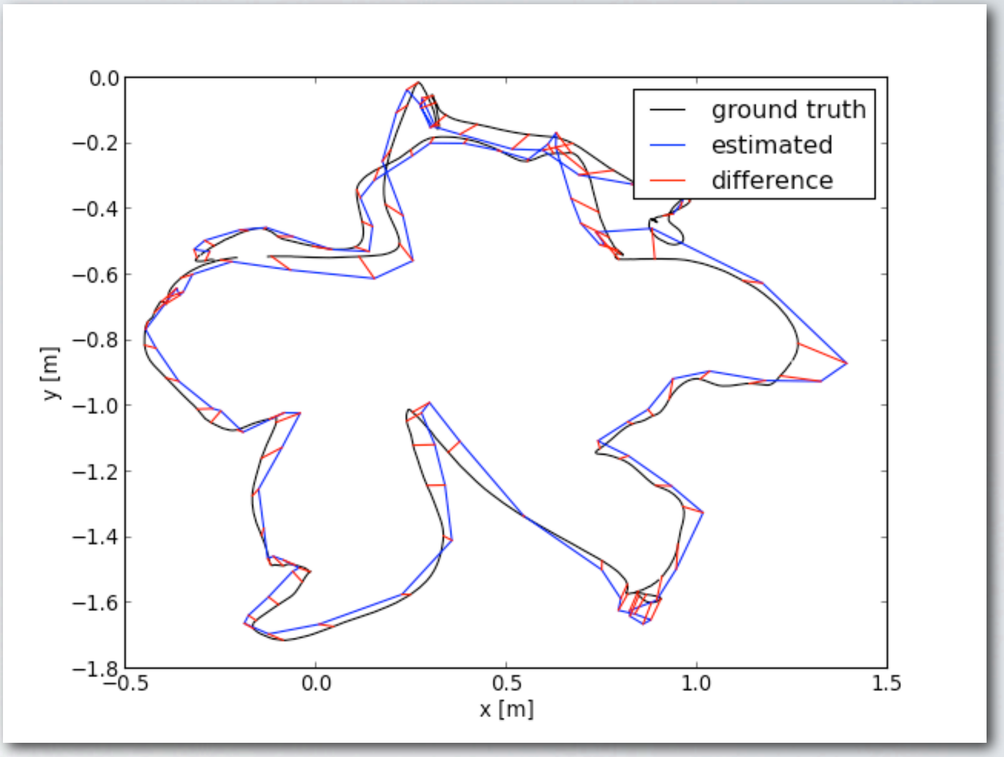
2. Joint Point and Plane Optimization

$$E = \alpha \sum_{i=0}^{N} [(p_i - q_i) \circ n_i]^2 + (1 - \alpha) \sum_{i=0}^{M} w_i [(1.0 - n_{src_i} \circ n_{tgt_i}) + \beta (d_{src_i} - d_{tgt_j})]^2$$

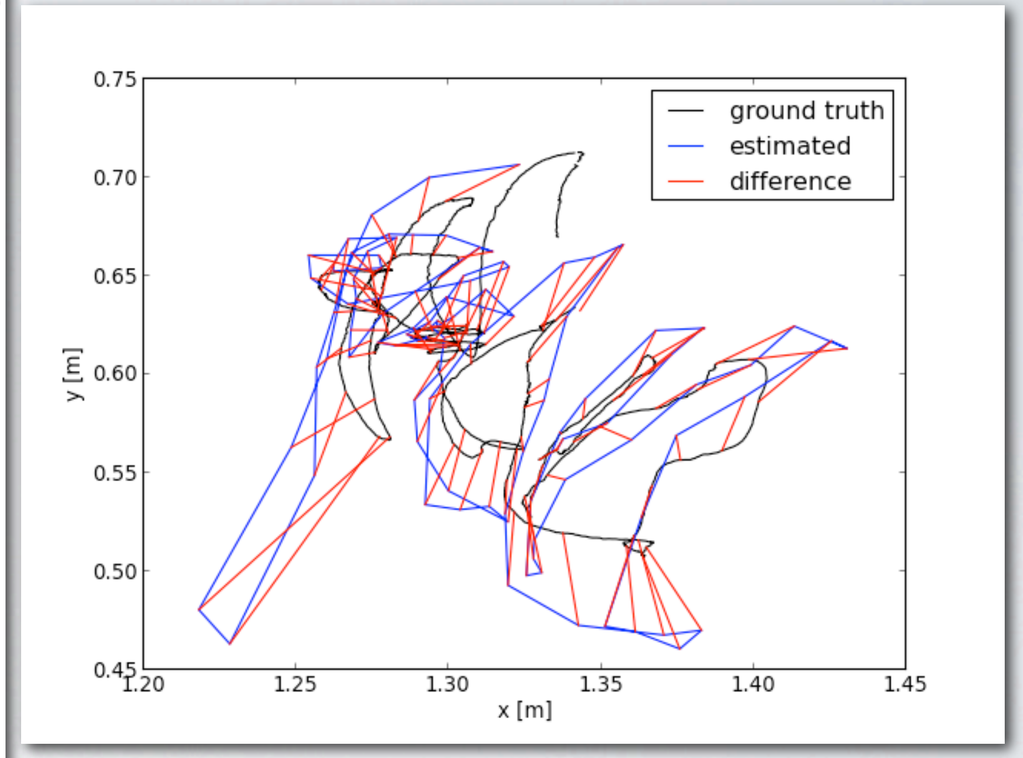
3. Plane-Constrained ICP

reduce the dimensionality of the solution space from 6D to 3D

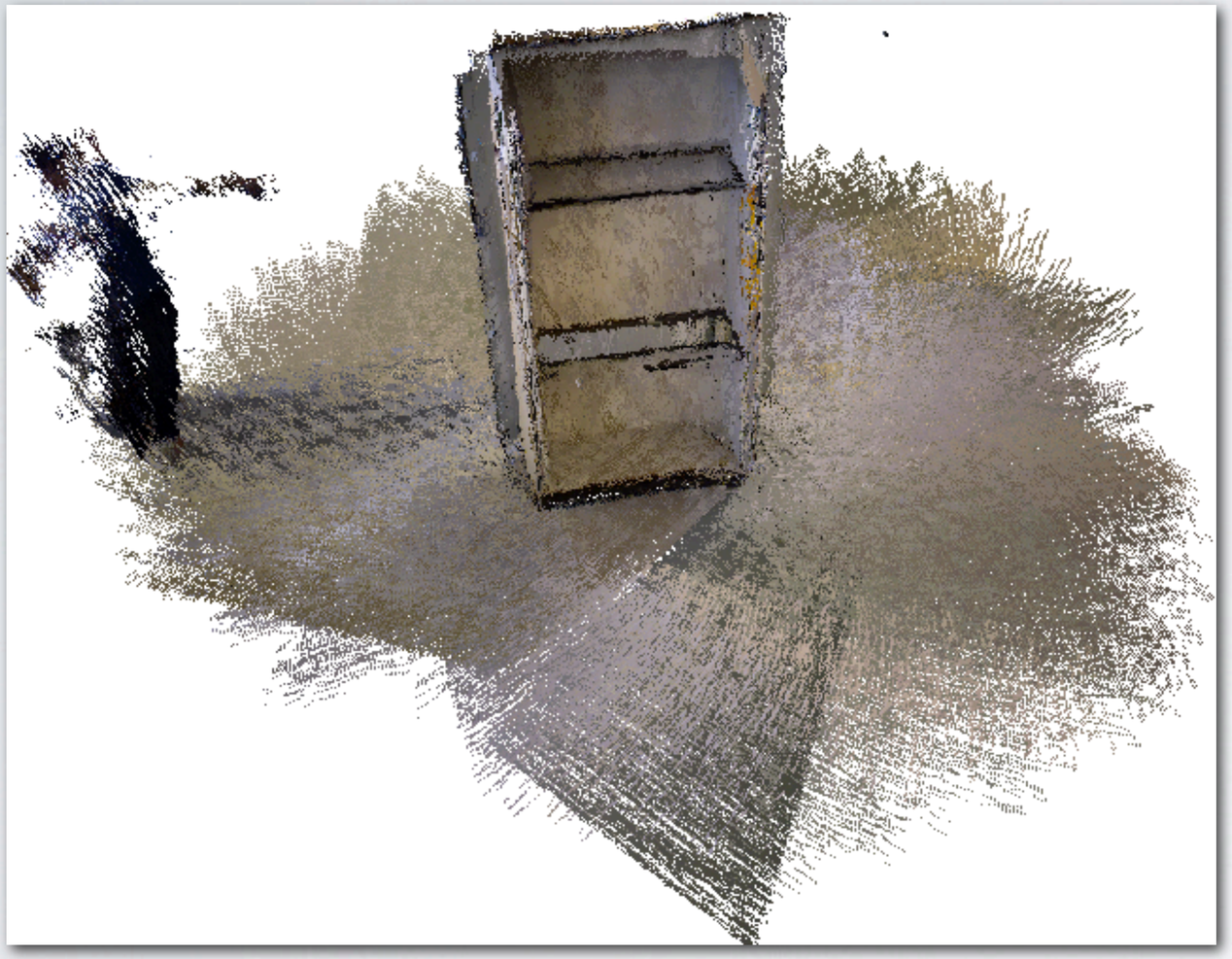
Planes

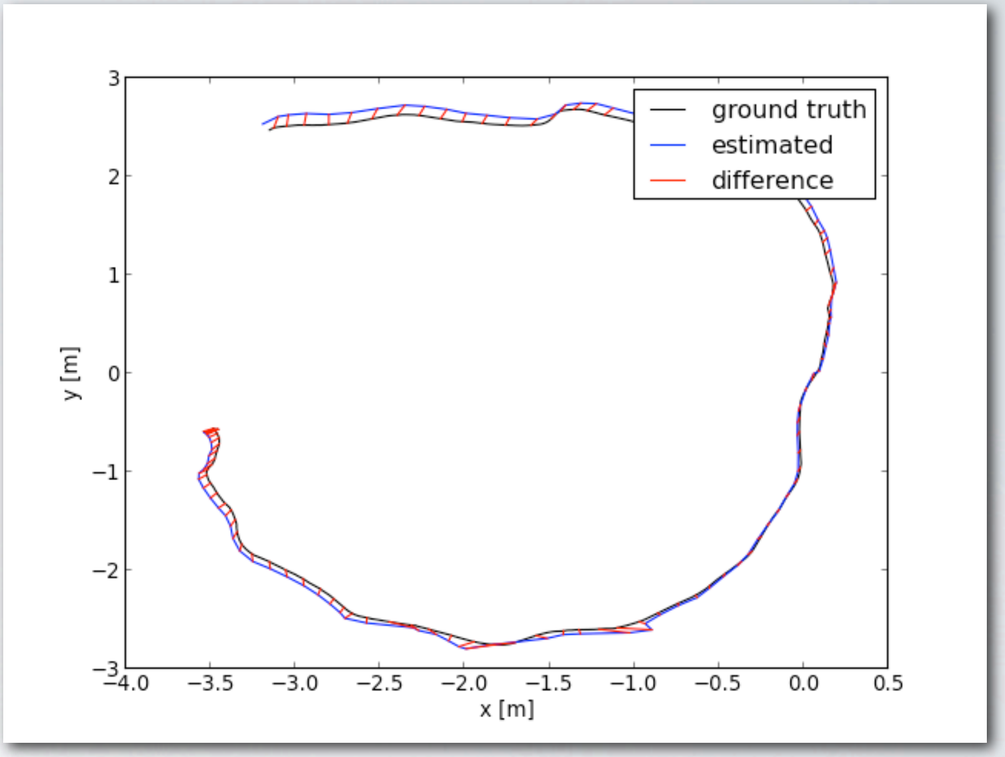


Results - SLAM

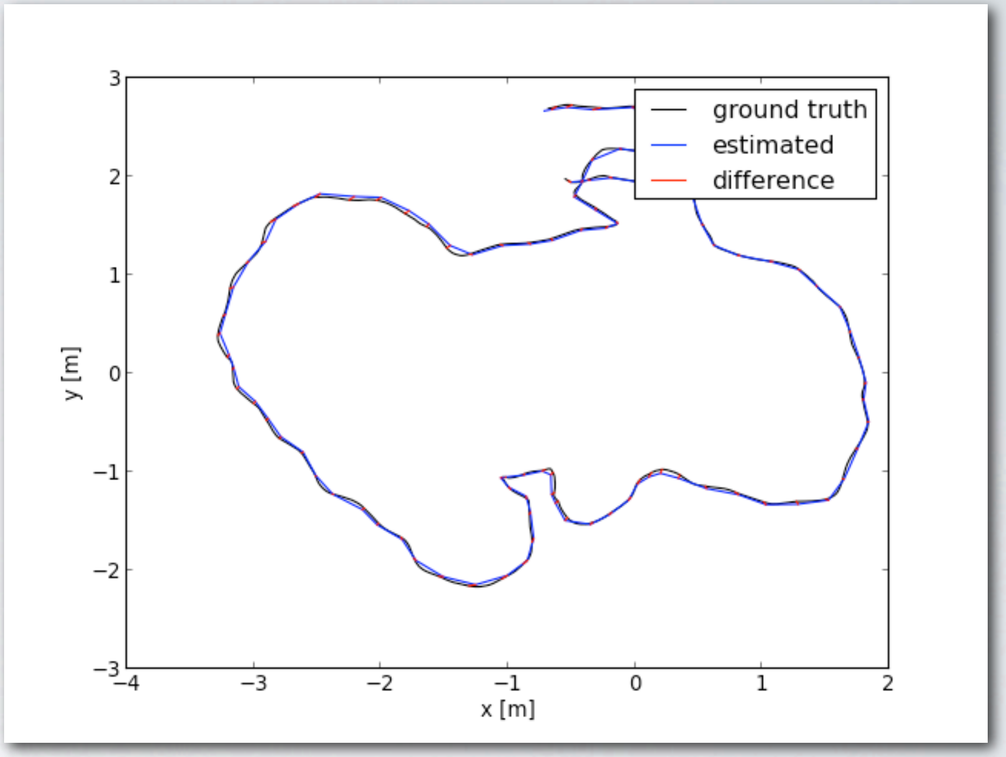


Results - SLAM

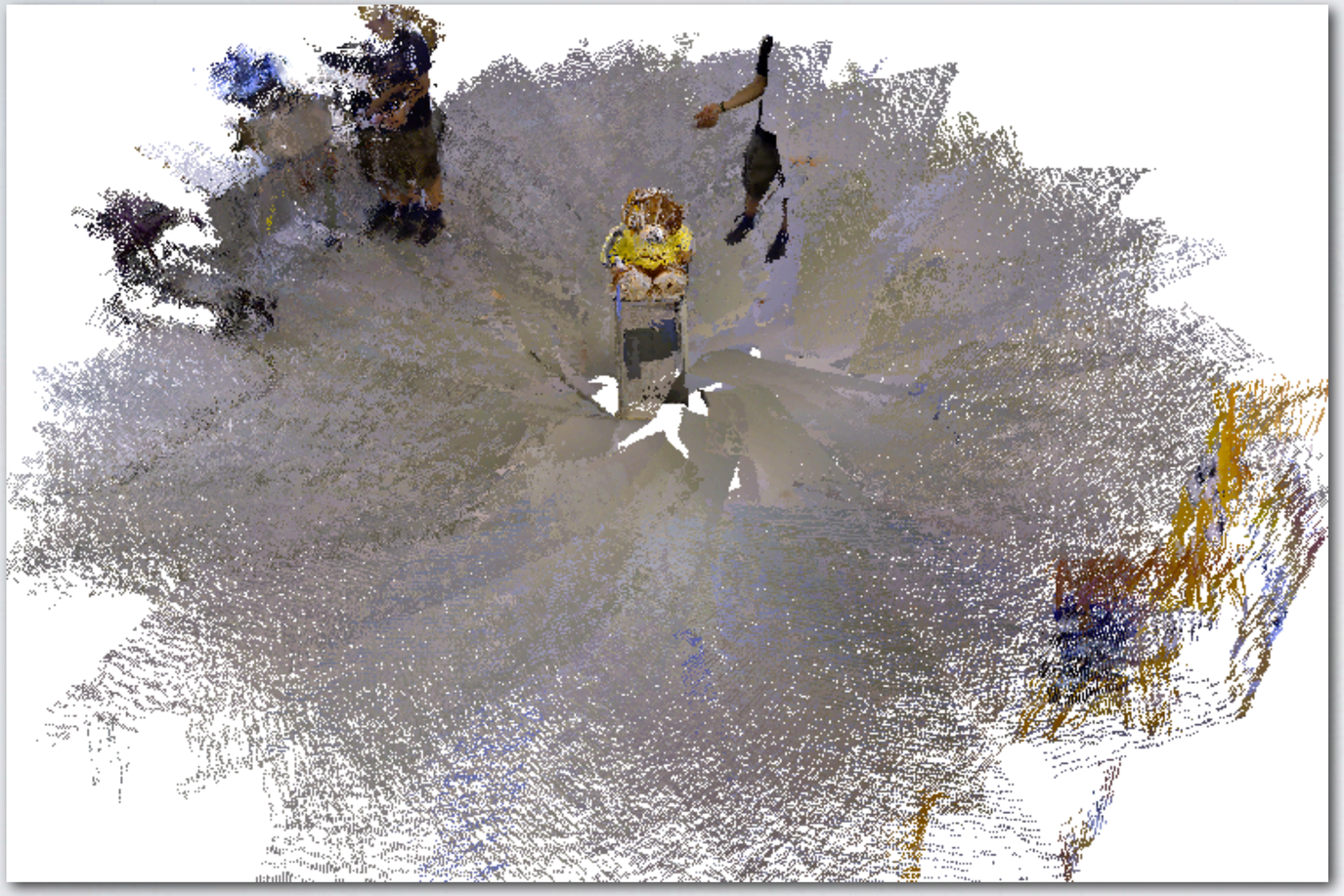


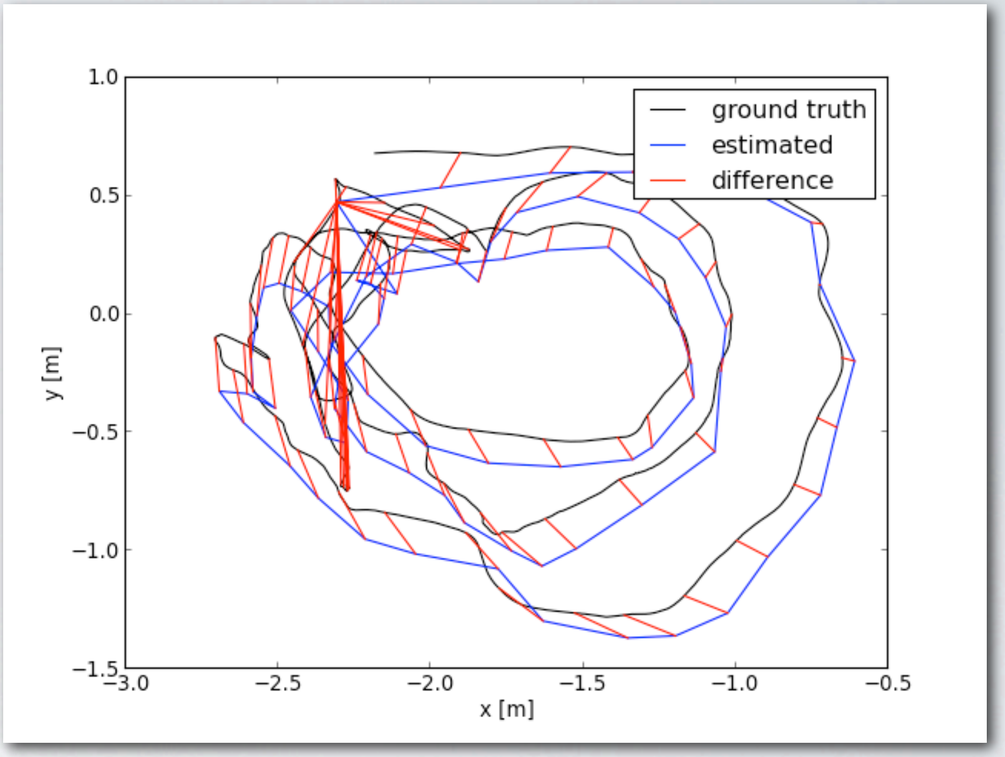


Results - SLAM

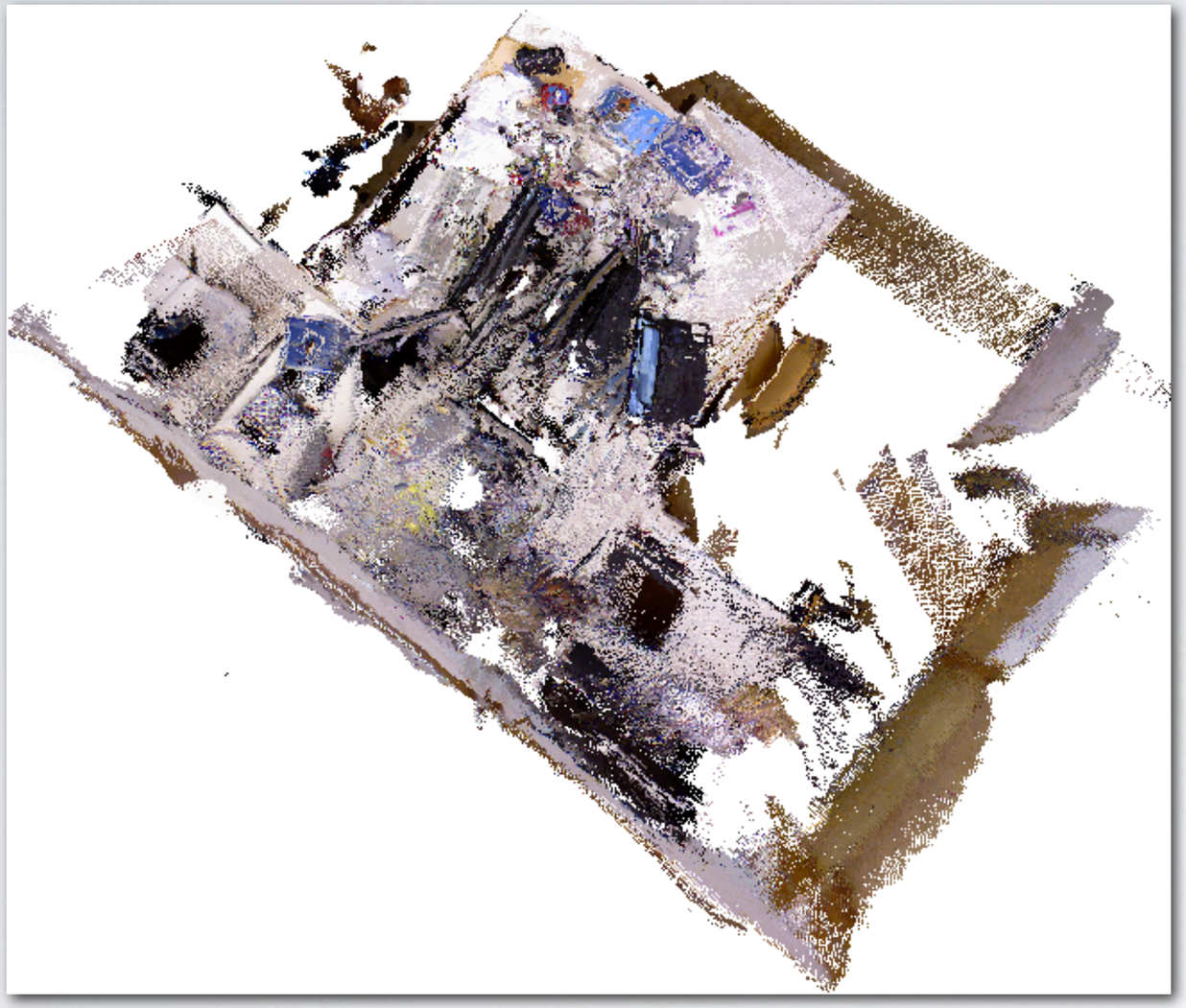


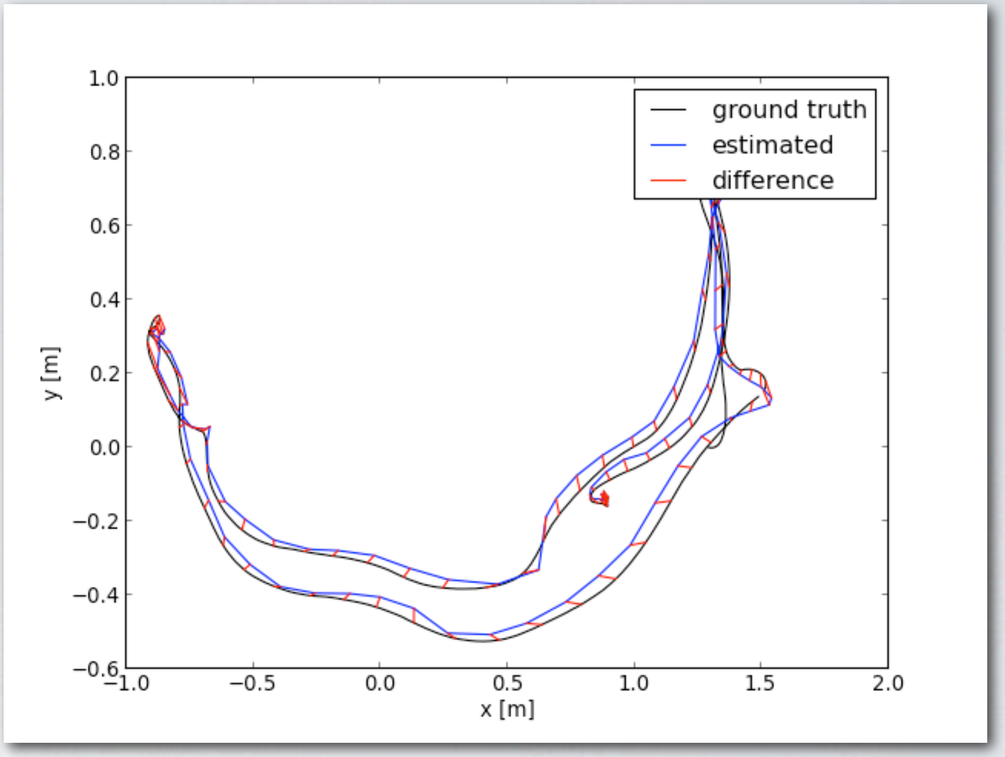
Results - SLAM



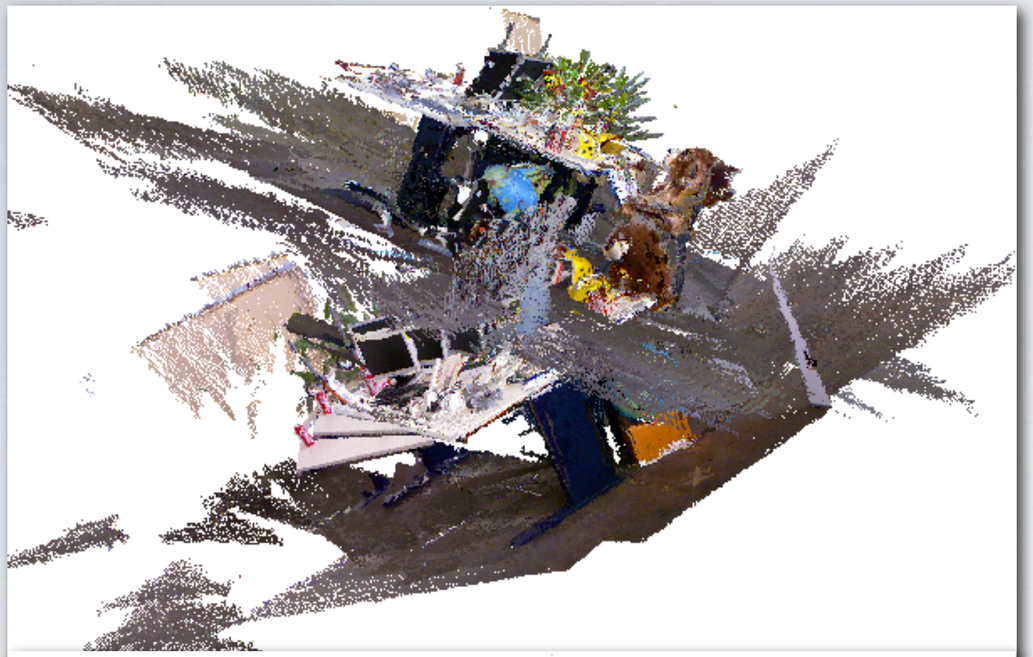


Results - SLAM

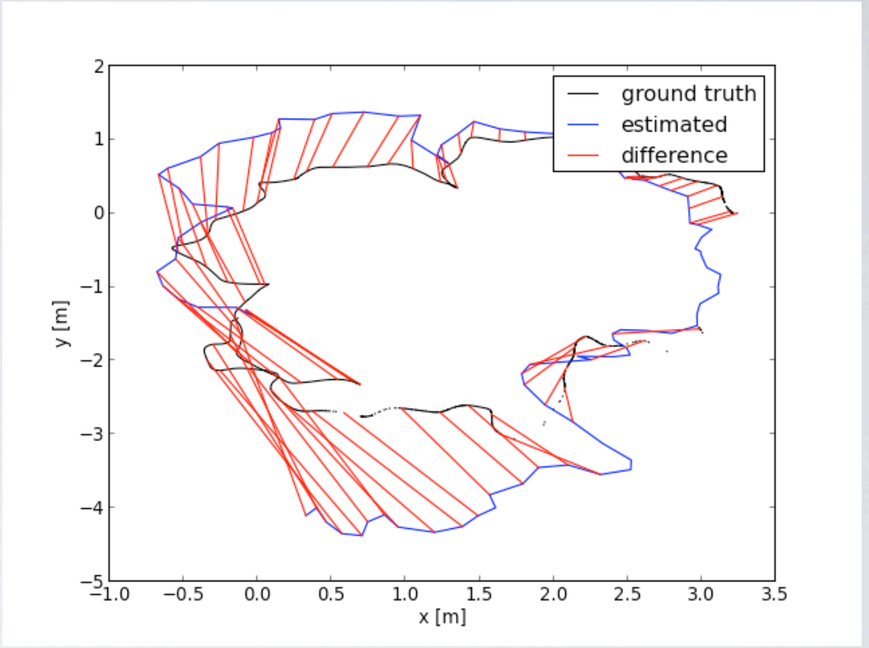




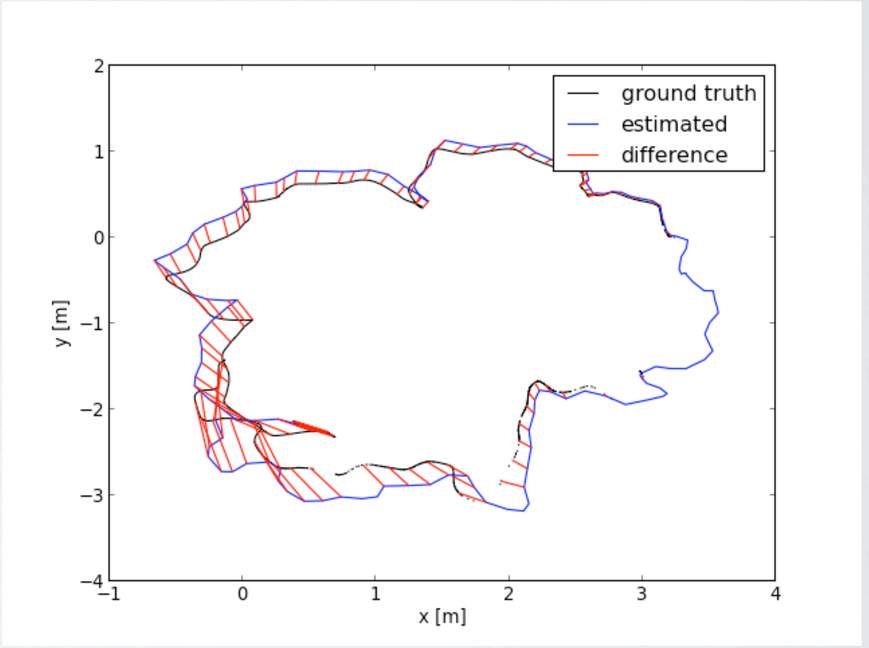
Results - SLAM



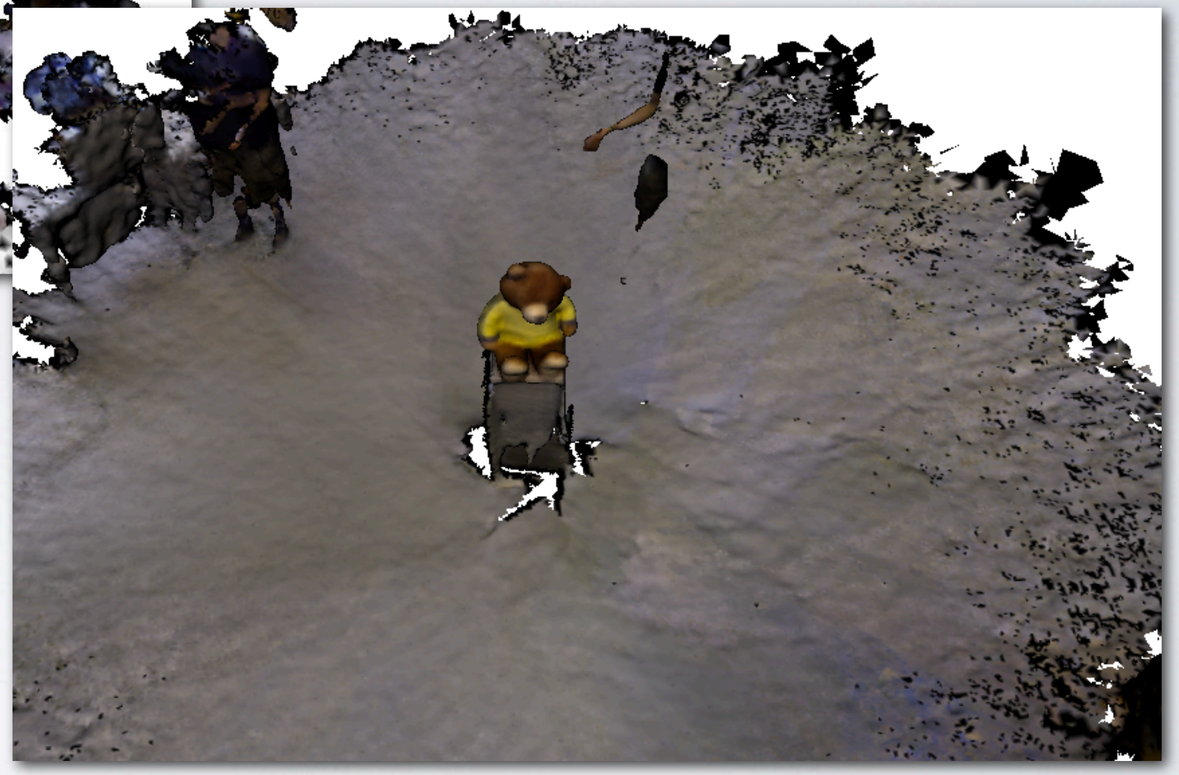
no planes



with planes



Results - SLAM



Results - Modeling

Results - Modeling

Results - Modeling