Interdimensional Robot Cooperation

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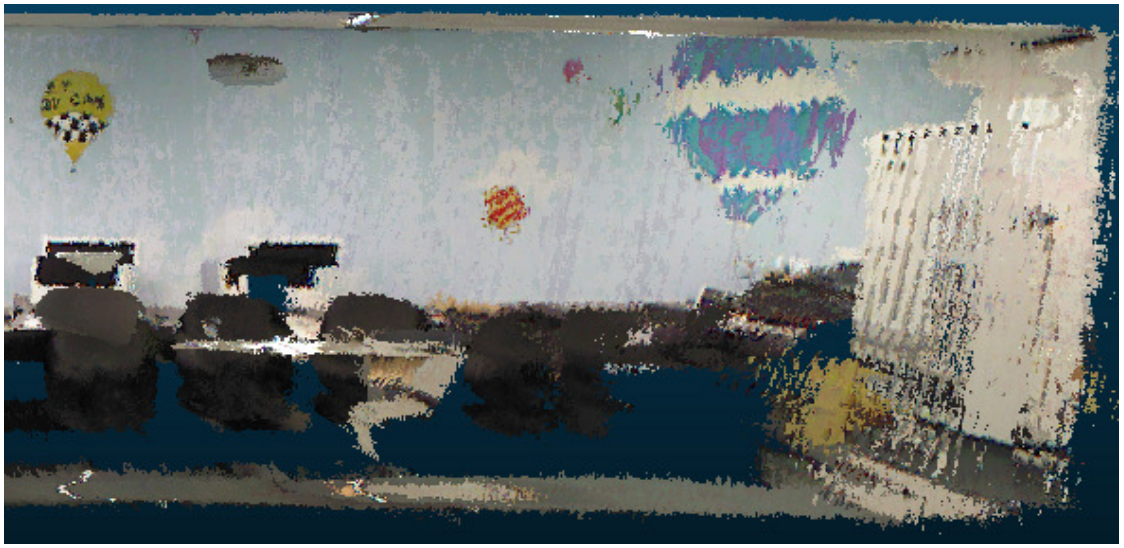
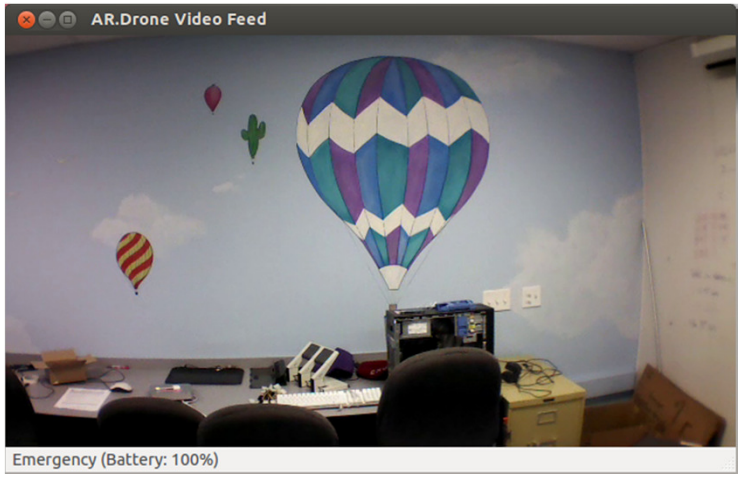
Jerry Hsiung, Cyrus Huang, Zakkai Davidson, and Zach Dodds

Now…

3d representations are a new standard for robot spatial reasoning, …





… yet 2d image sensing is still common – *and will certainly continue to be for a long time.*

… vs. Then

Cooperating?!

2d sensors

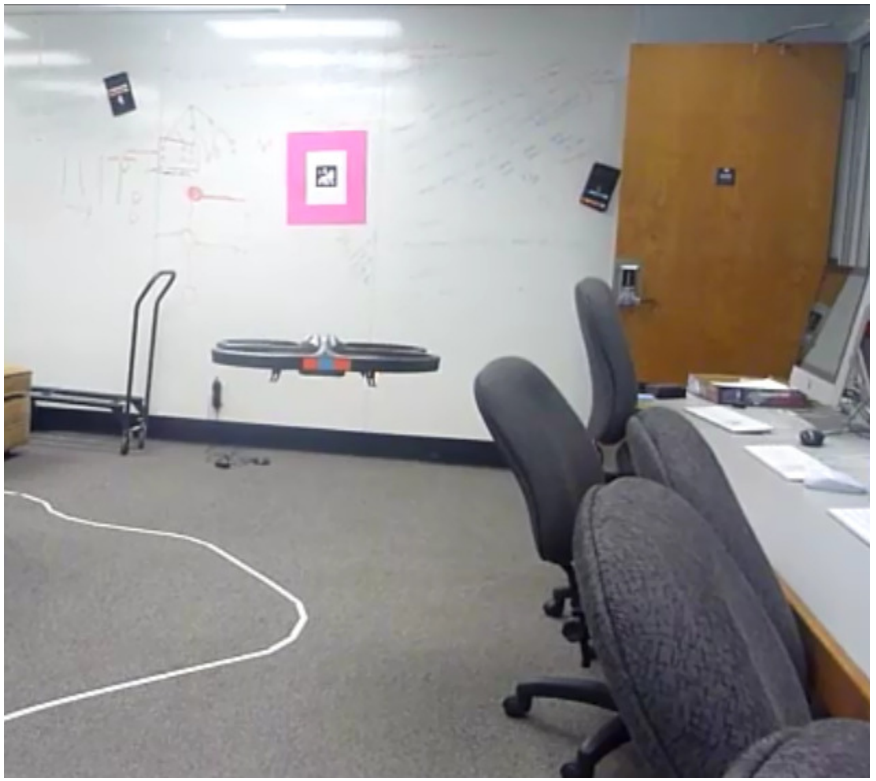
3d models

Our goal: to investigate robot platforms, software, and algorithms for ***using 2d sensors amid 3d models*** of the world.

Two concrete challenges…

more ***robust*** navigation

more ***general*** "lab escape"



bridging 2d sensors with 3d spatial representations

New platform: *Neato*

Initial tasks

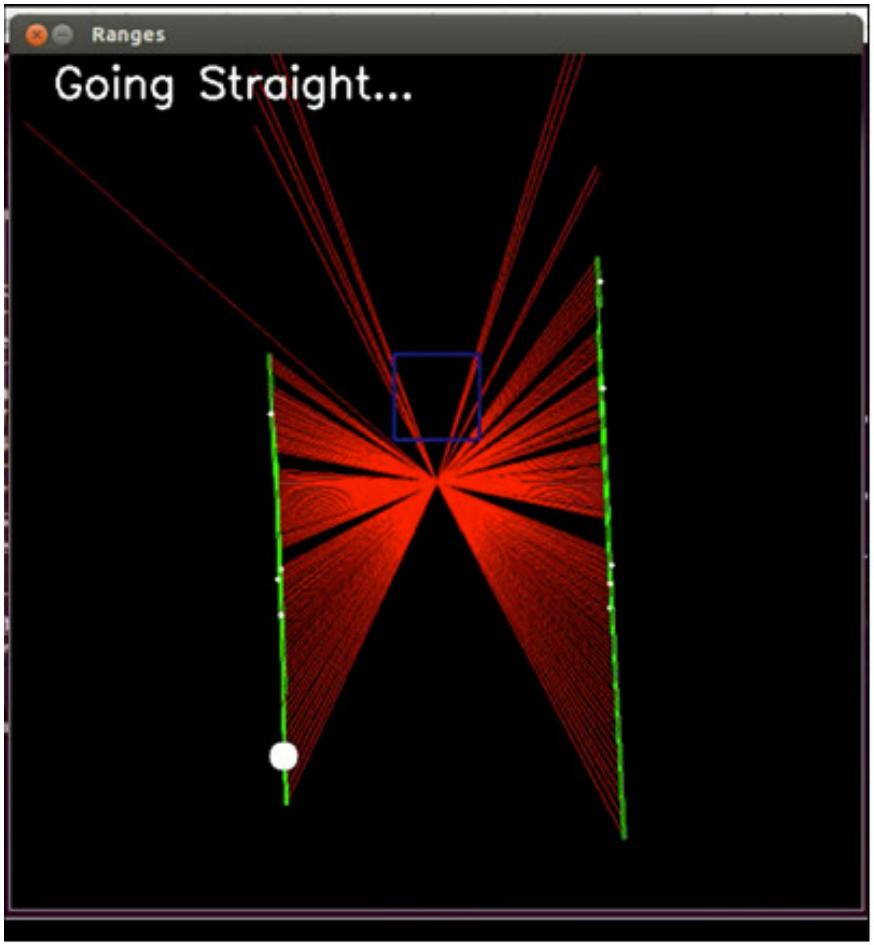
- **learn ASCII API**
- **write device drivers**
- interpret sensor data
- follow corridors
- detect intersections

AI Tasks

- pt-to-pt navigating
- localize and navigate
- minimize ambiguity
- navigate predictively
- build 2d and 3d maps

Objective: to get this robot **running** and **reasoning**

New platform: *Neato*



Initial tasks

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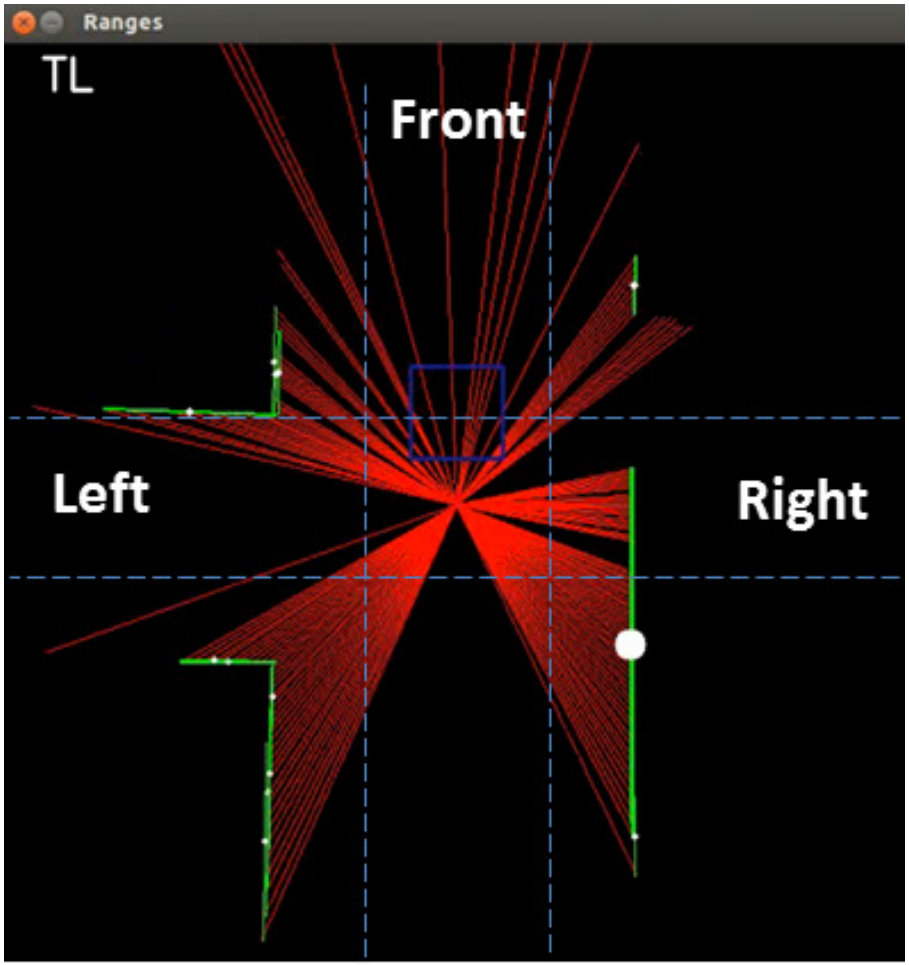
- write device drivers
- **interpret sensor data**
- **follow corridors**
- detect intersections

laser-scan data, estimated walls, *"aligning"* wall

New platform: *Neato*



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AI Tasks

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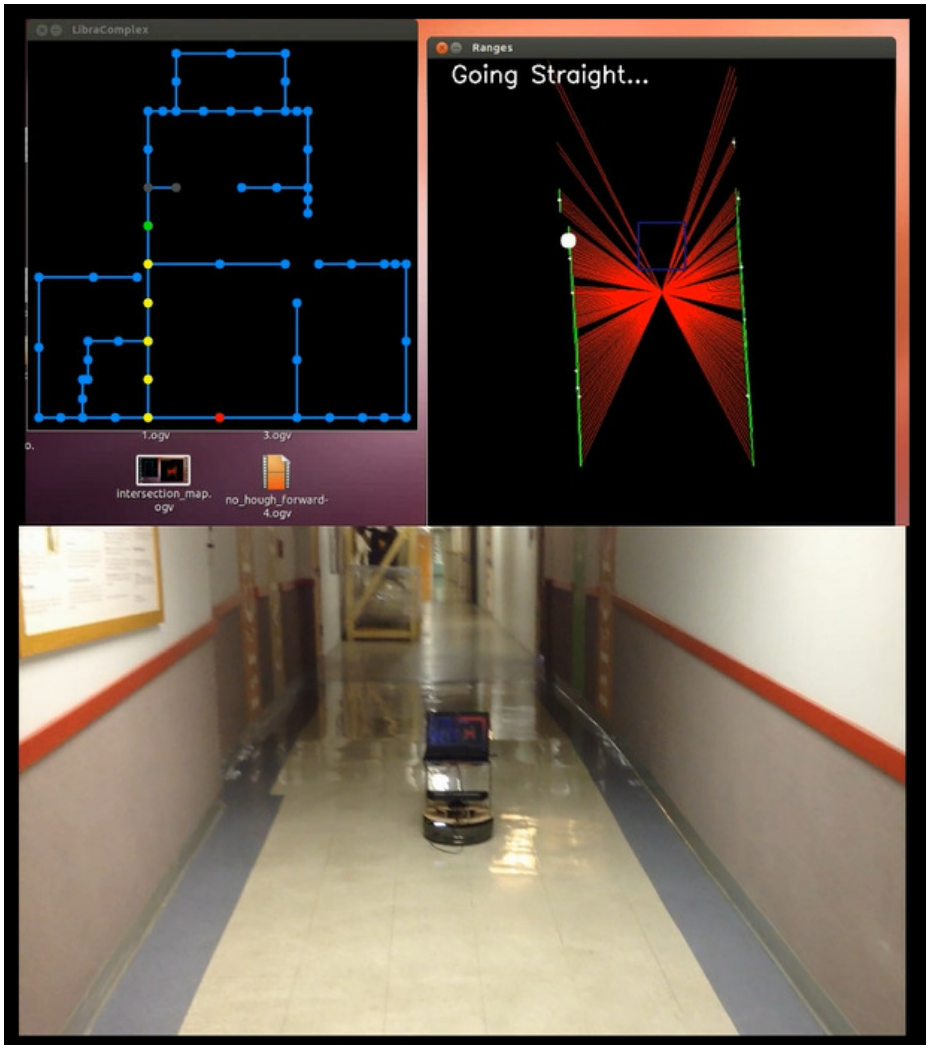
wall-placement determines intersection ***type***

Neato *navigation*



robot_navigation_known_start

navigating the Libra complex, ***with the start node given***

Localization

What if the robot doesn't know its starting pose?

map with all nodes large
and the goal node in red

how many possibilities will
remain?

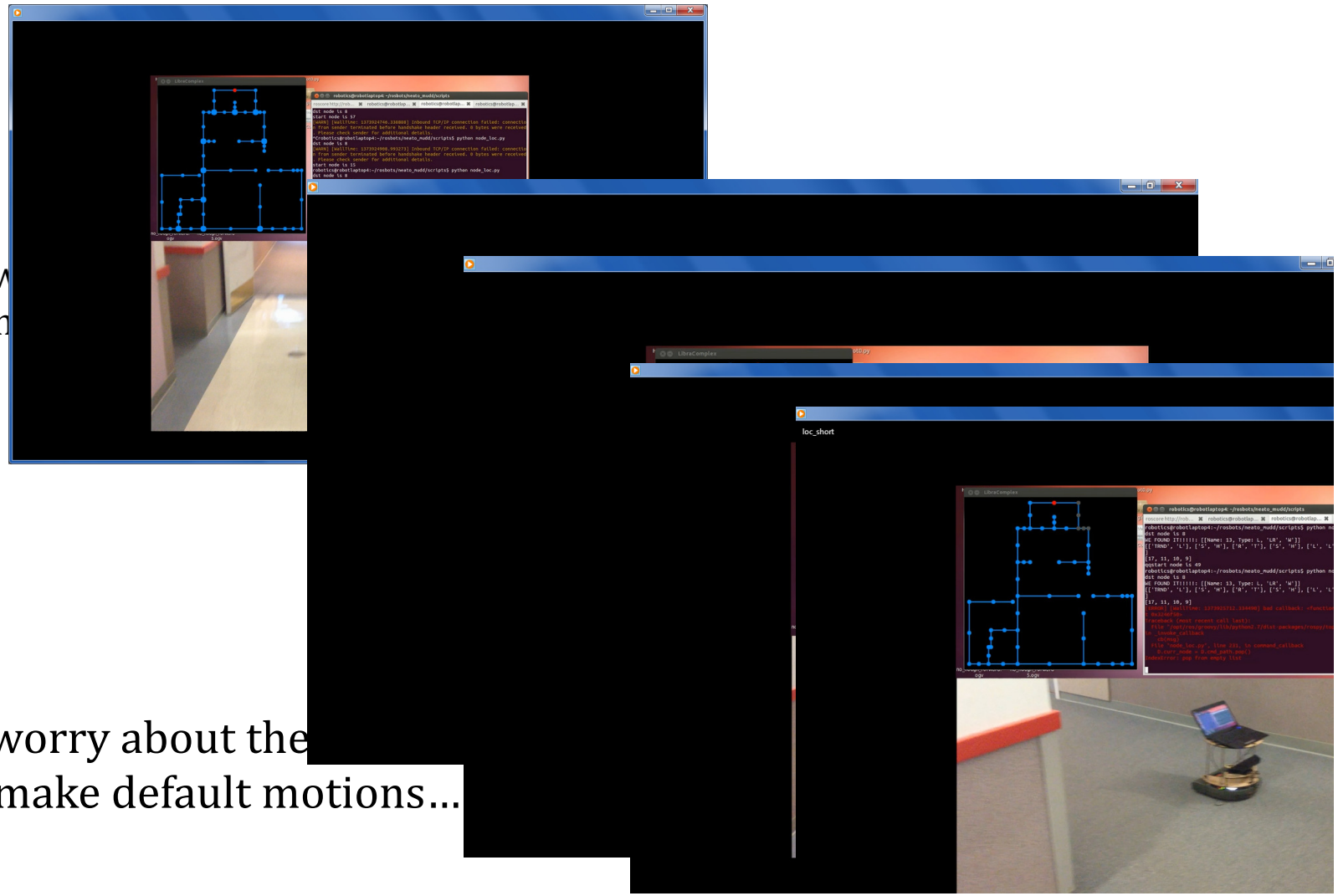
move to the…?

Don't worry about the goal.
Instead, make default motions…

Localization

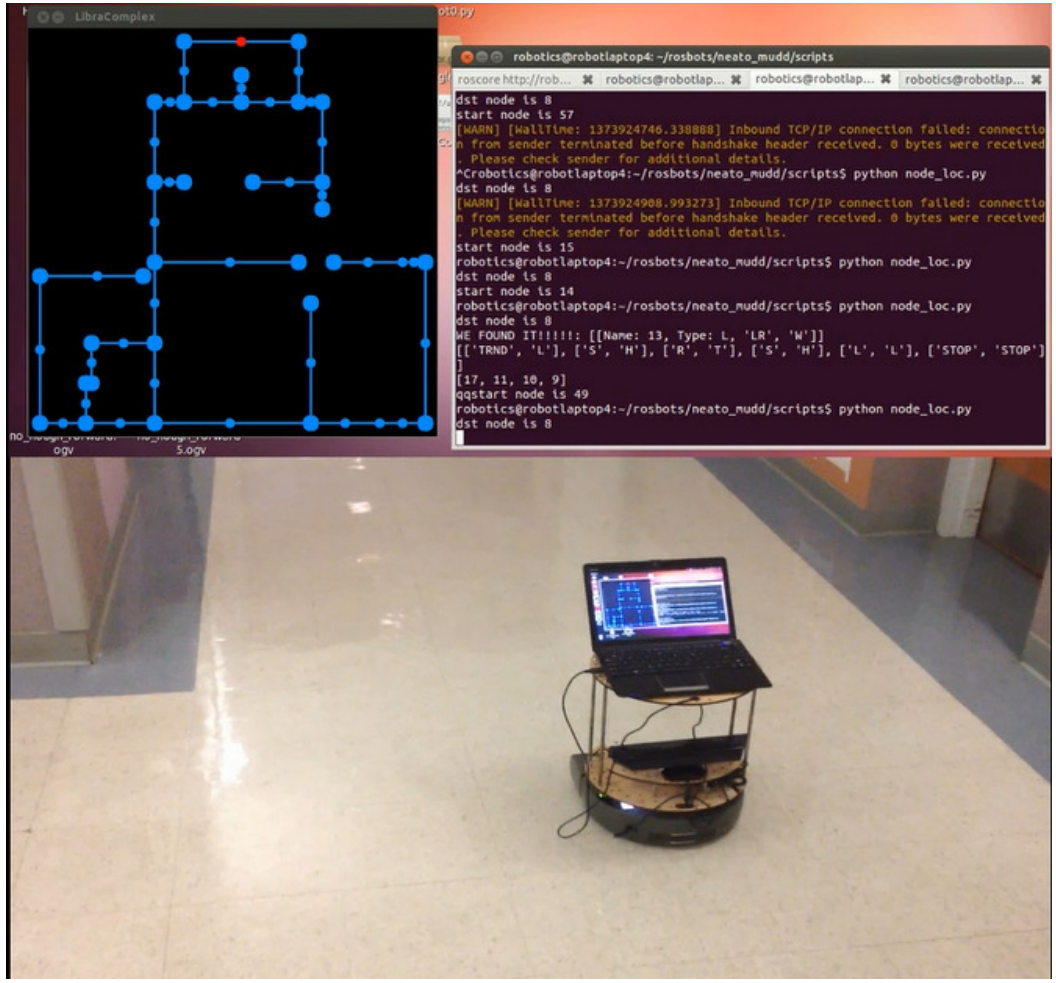
What if the robot doesn't know its starting pose?

map w
and th



Don't worry about the
Instead, make default motions…

Markov localization



loc_short.mp4

navigating to a goal ***without* the start node given**

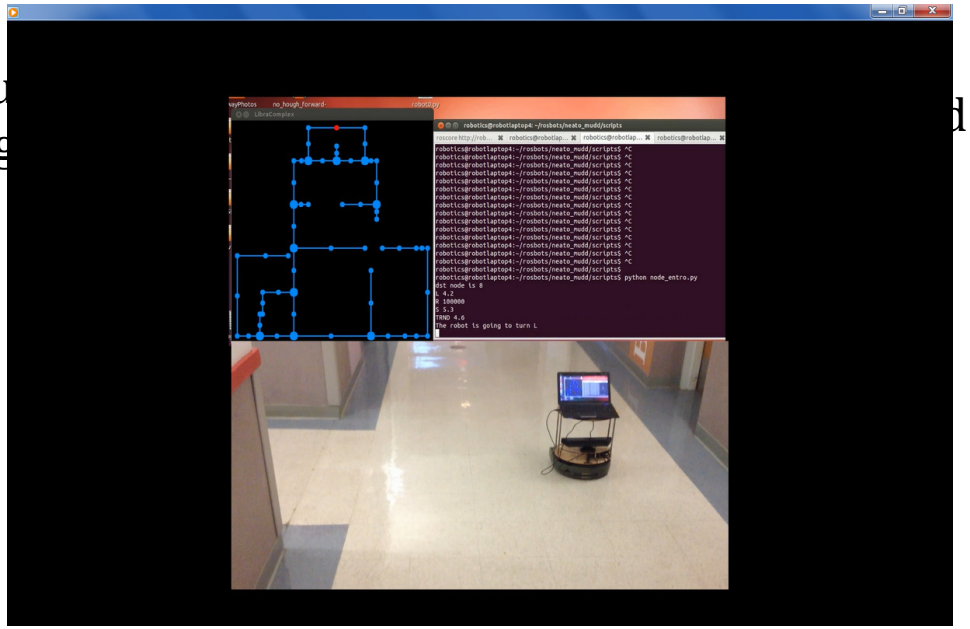
Can we be more *deliberate*?

Each intersection offers a choice:

Which turn to make, *even if the robot isn't sure where it is*?

map of cu

knowledg



d it go?

Can we be more *deliberate*?

Each intersection offers a choice:

Which turn to make, *even if the robot isn't sure where it is*?

map of current knowledge…

Possible results if the robot heads straight

Possible results if the robot turns the corner

Possible results if the robot reverses course

Consider all of the possible *distributions* of results…

Entropy

~ the ***expected*** amount of information available from a distribution of possibilities.

example 1 bit

example of 2 bits

example of 1.05 bits

in general

Entropy-based localization

Each intersection offers a choice:

Which turn to make, *even if the robot isn't sure where it is*?

map of current knowledge…

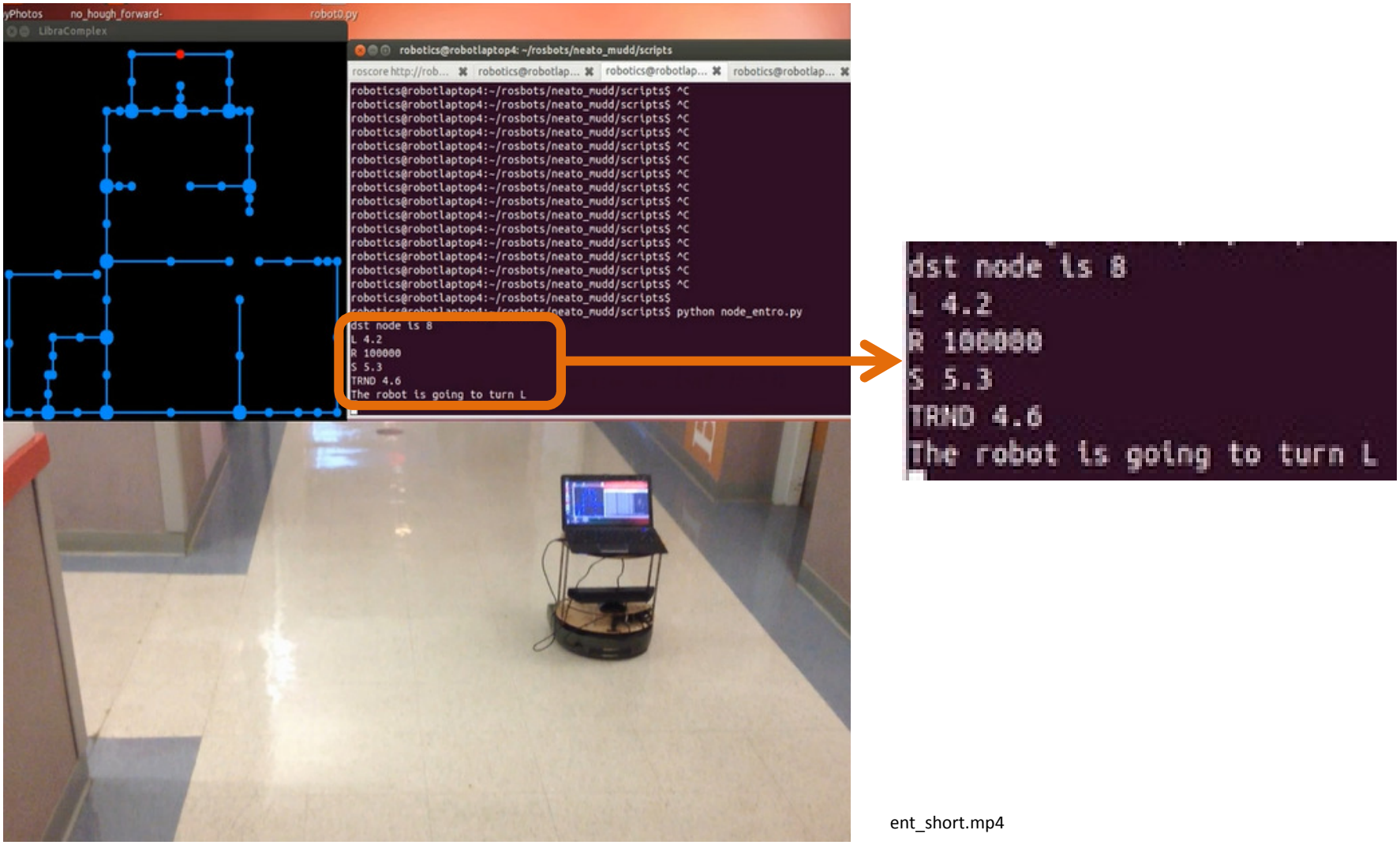
Possible results if the robot heads straight — bits

Possible results if the robot turns the corner — bits

Possible results if the robot reverses course — bits

We choose the action with the greatest ***expected information***.

Entropy-based localization



ent_short.mp4

Could we be **bolder**?

Leap before you look.

~ W. H. Auden

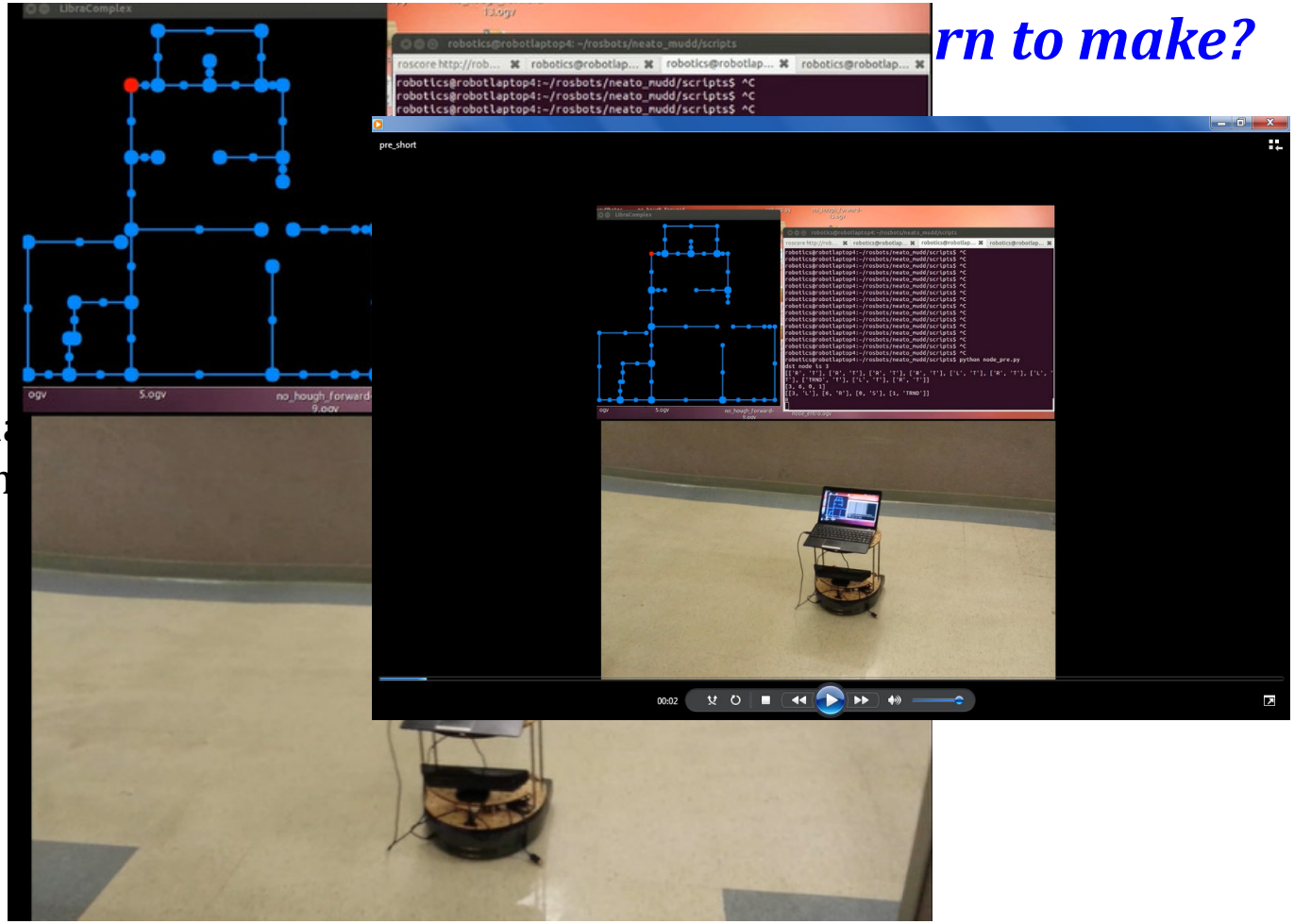
Just do it.

~ Nike

… perhaps if robots felt more contemplative.

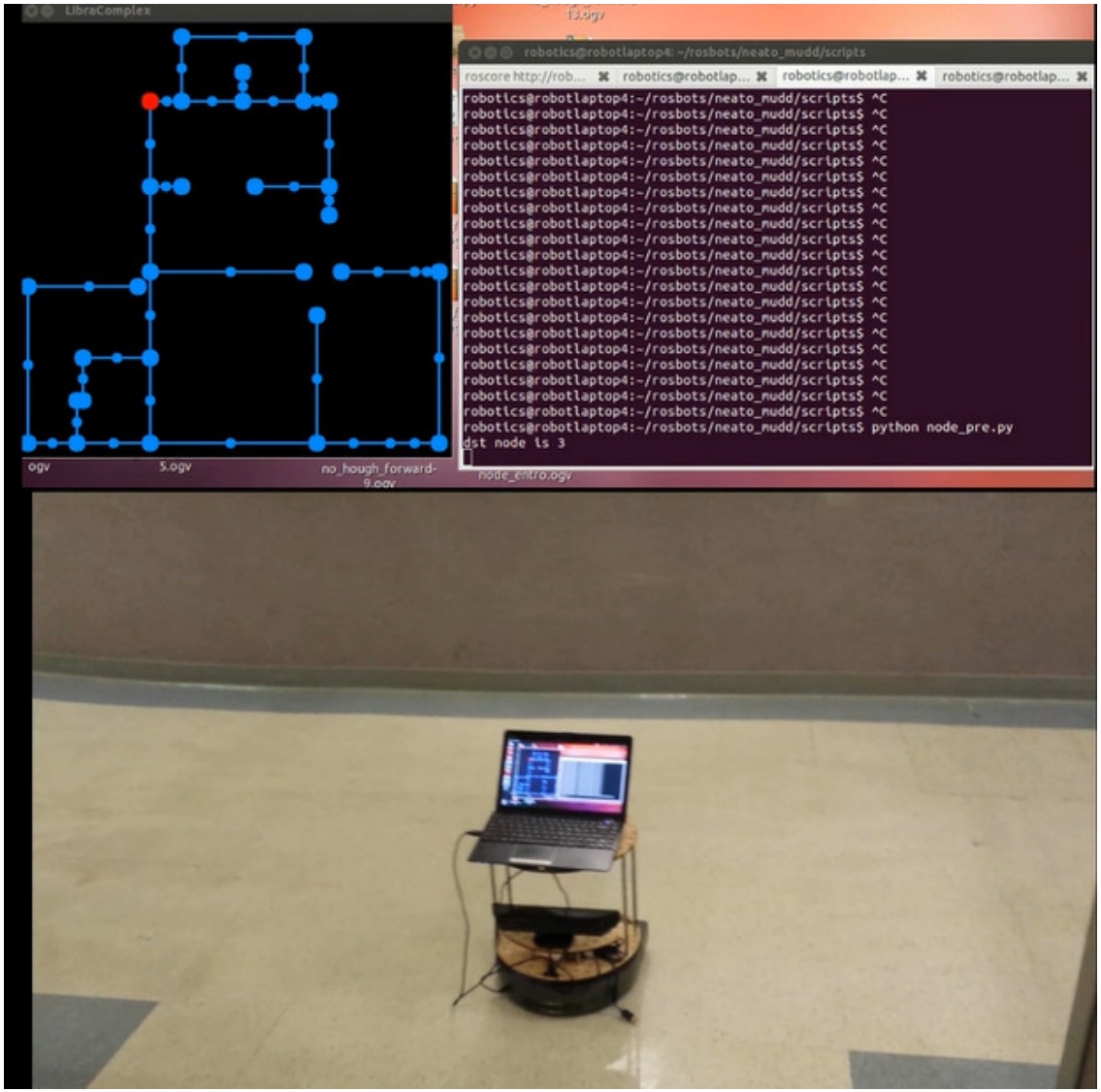
Predictive path planning

rn to make?



We could opt for the turn ***most likely to make progress toward the goal***.

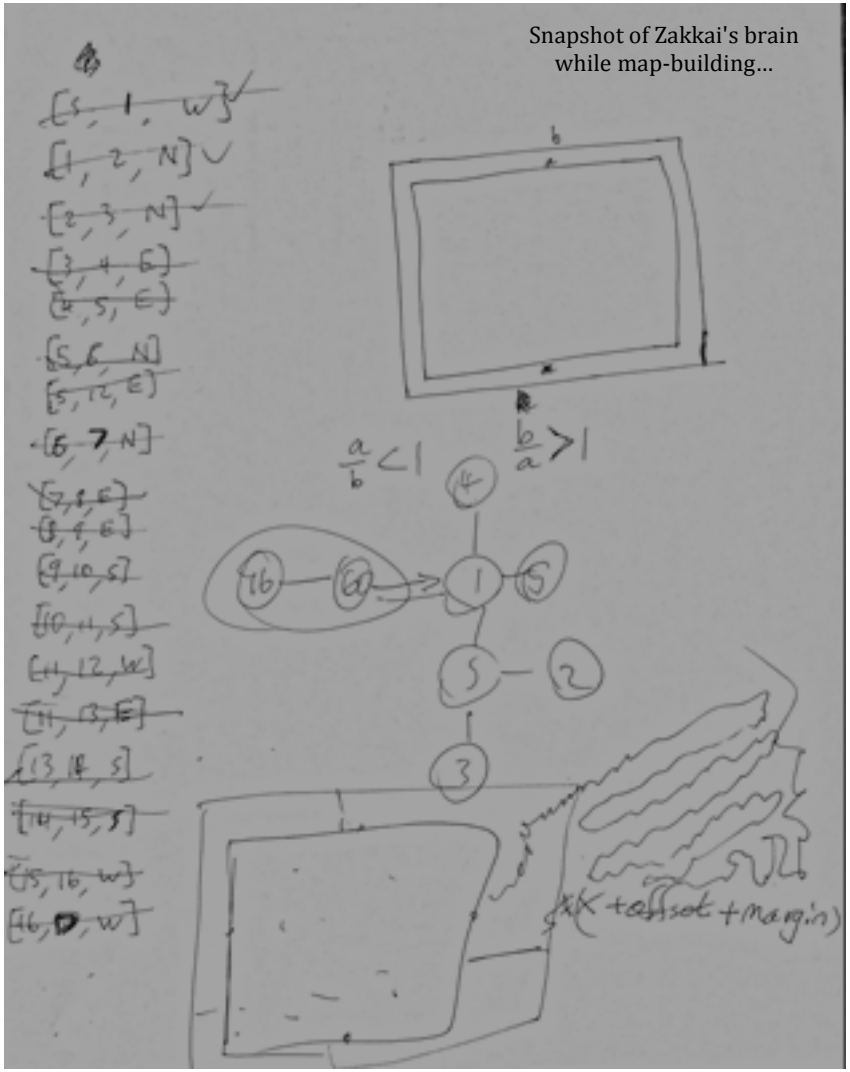
Predictive path planning

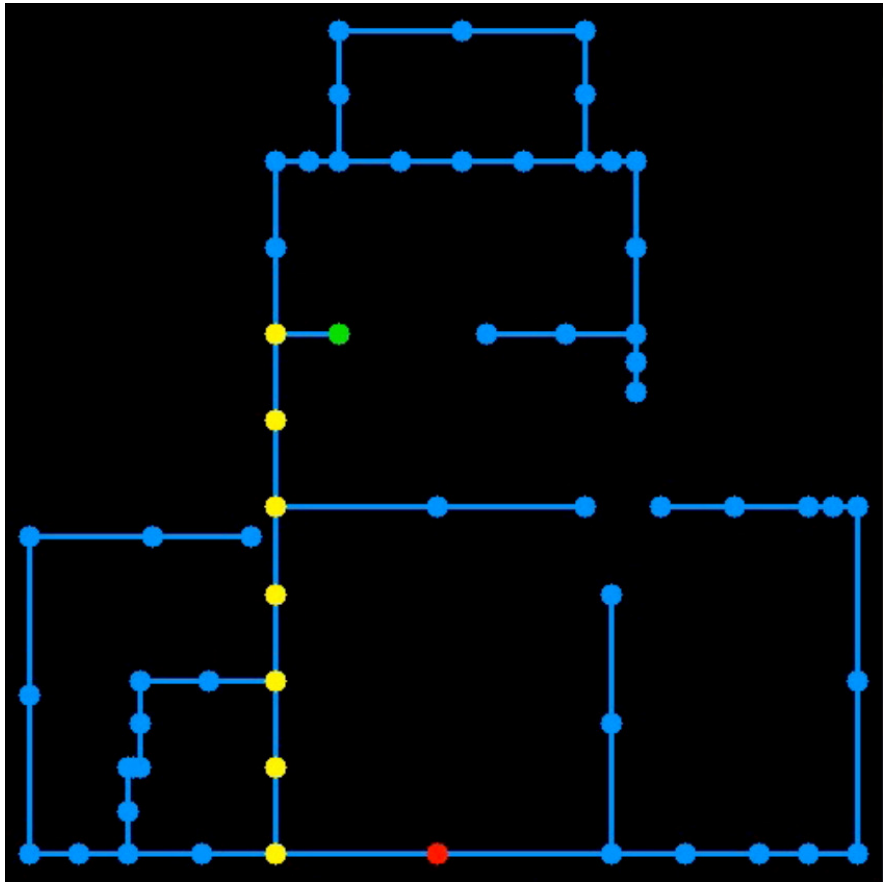


pre_short.mp4

more robust navigation ~ *but all with a hand-built map*

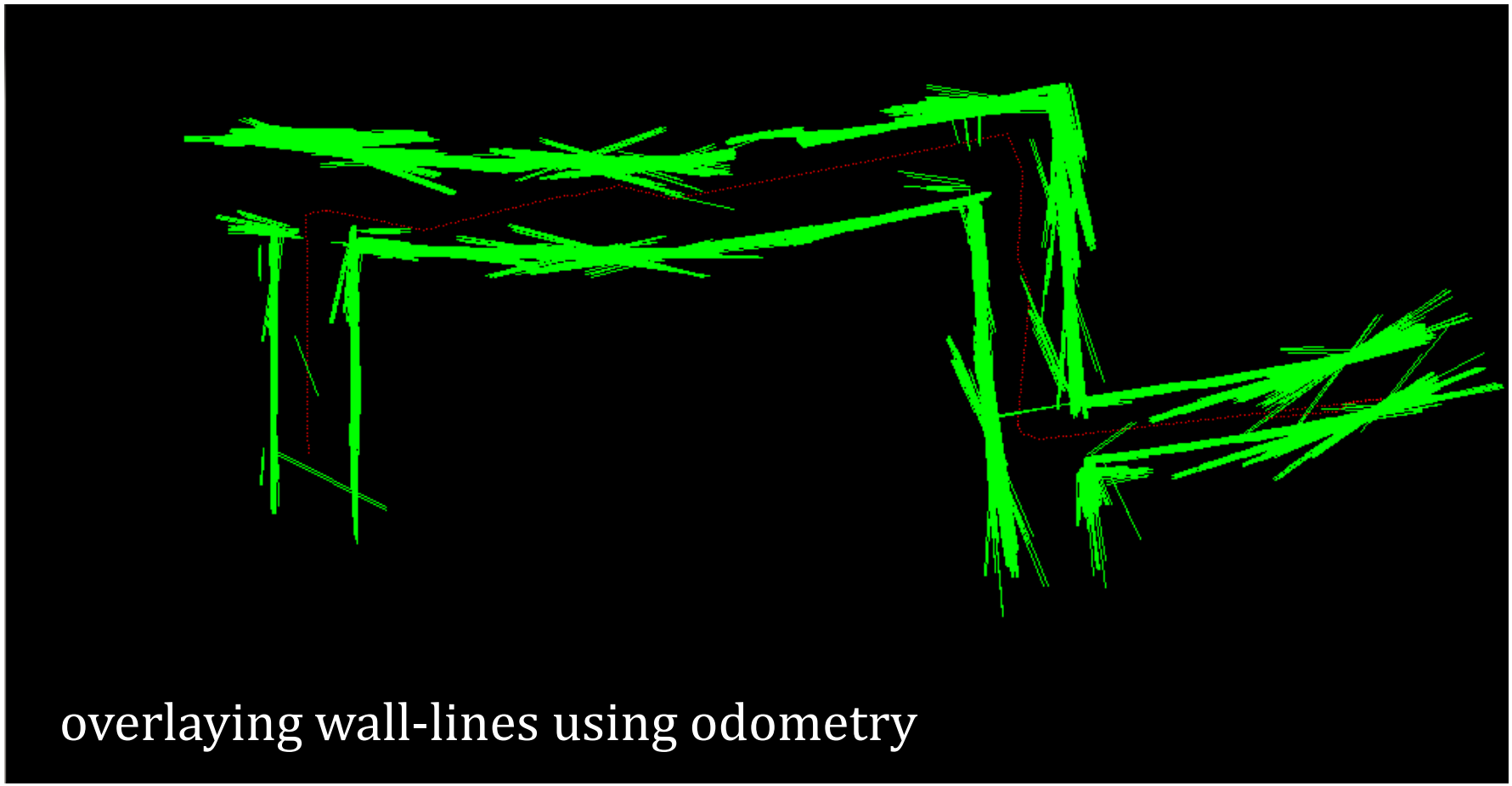
Map-building





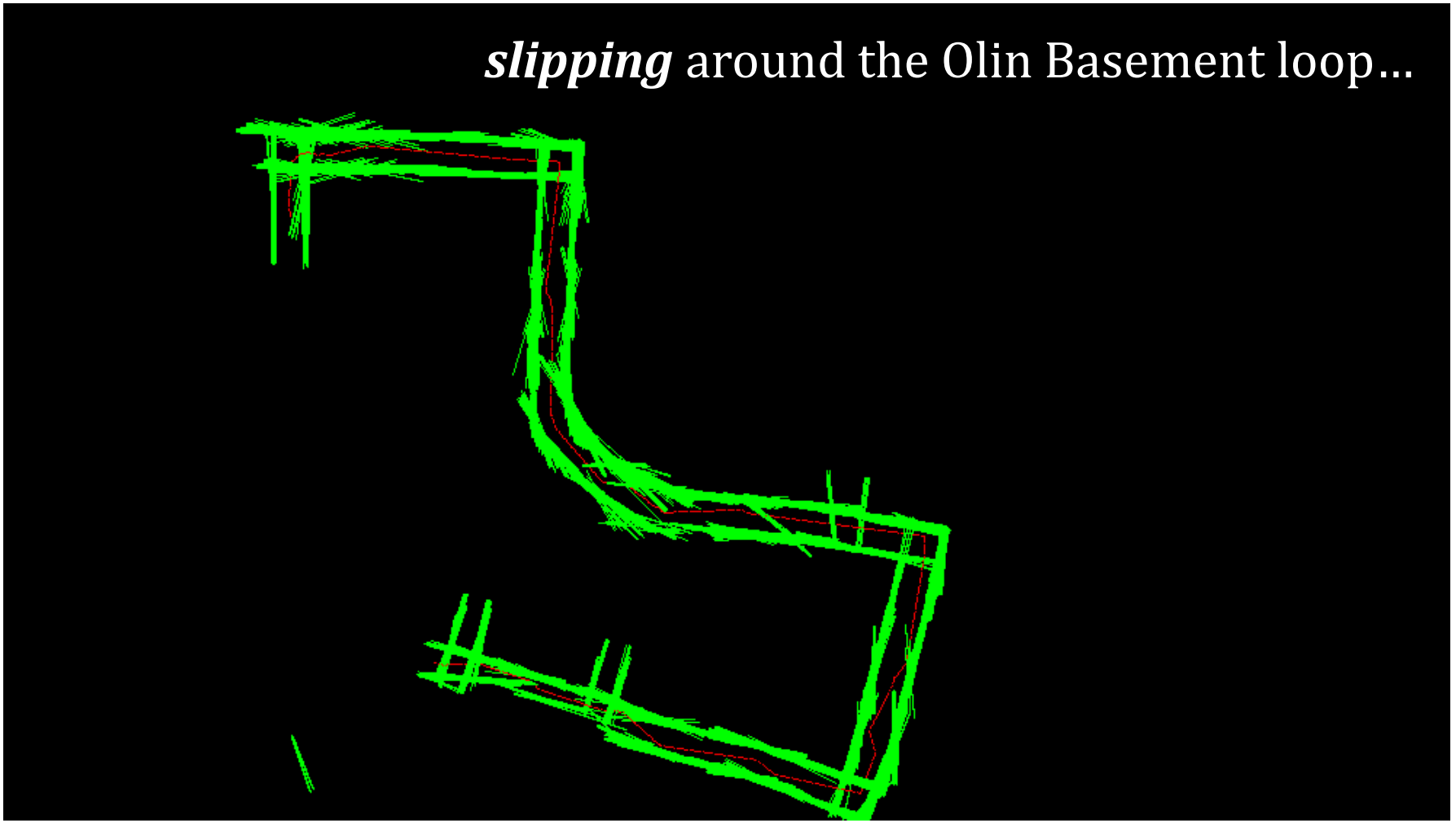
Ideally, mapping would be ***automated***, as well…

Autonomous Mapping



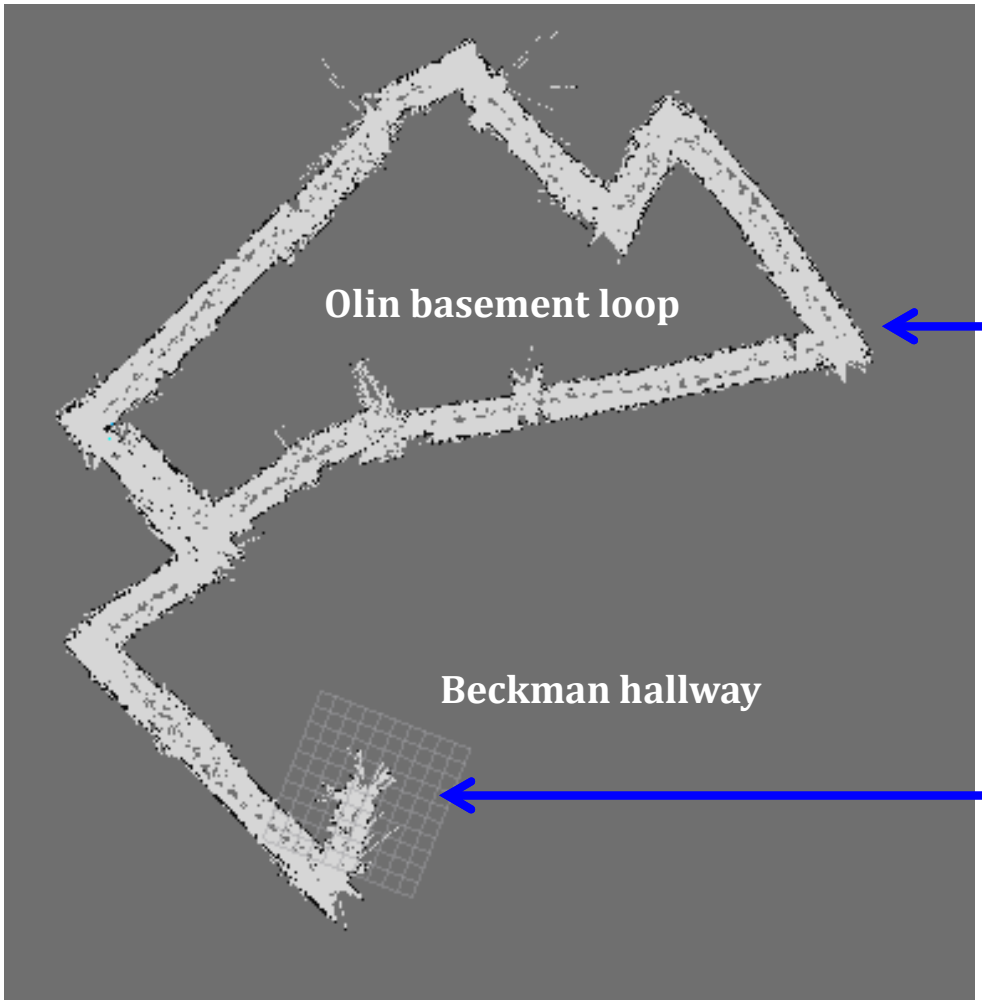
overlaying wall-lines using odometry

Mapping



`gmapping`

an algorithm for autonomous laser-based mapping



(1) adjust each scan's pose to best-fit previous scans

straightens corridors

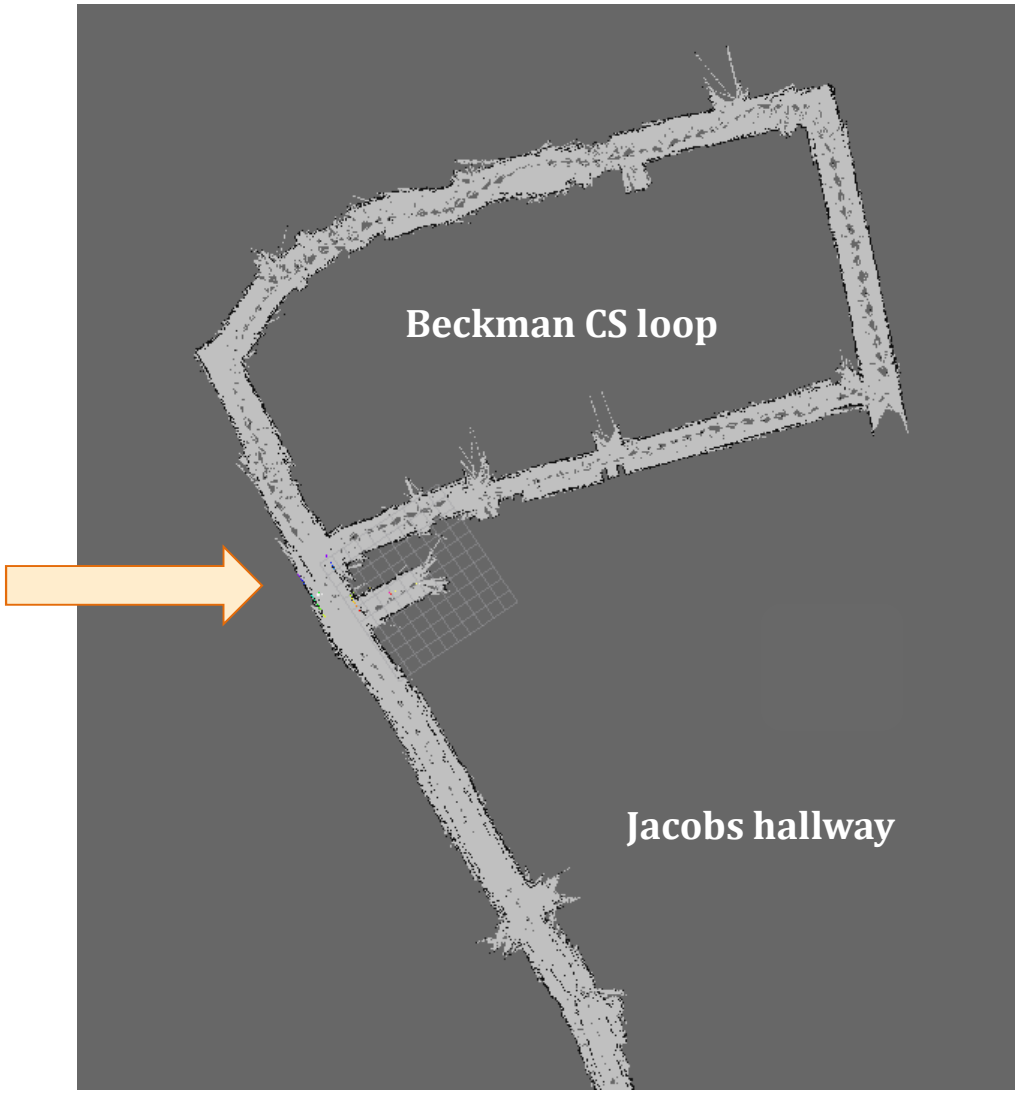
(2) search for distant-past similarities to "close loops"

corrects slippage?

gmapping

... can *miss* "obvious" loops

Laser scans aren't very "***distinguished***."



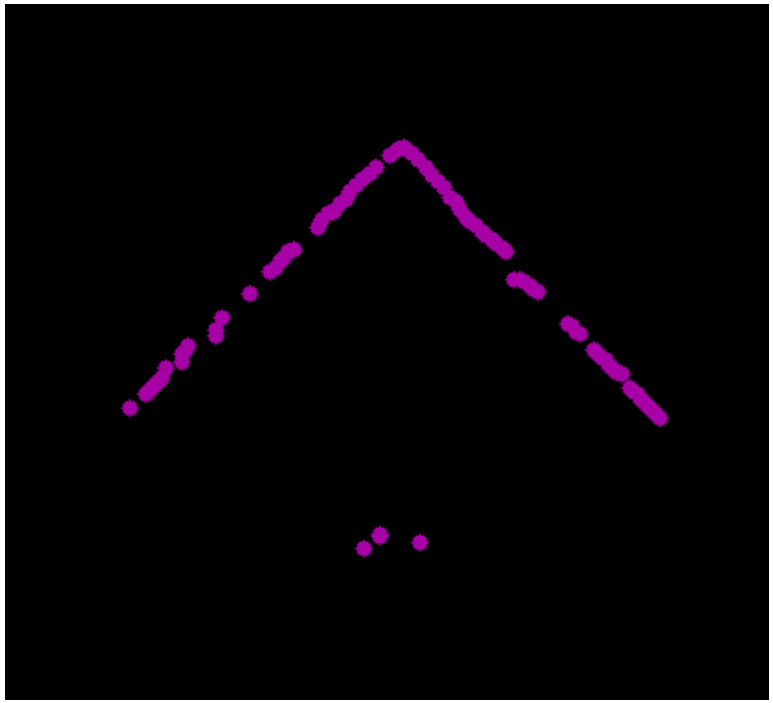
More distinct
landmarks would help...

... probably texture in 3d

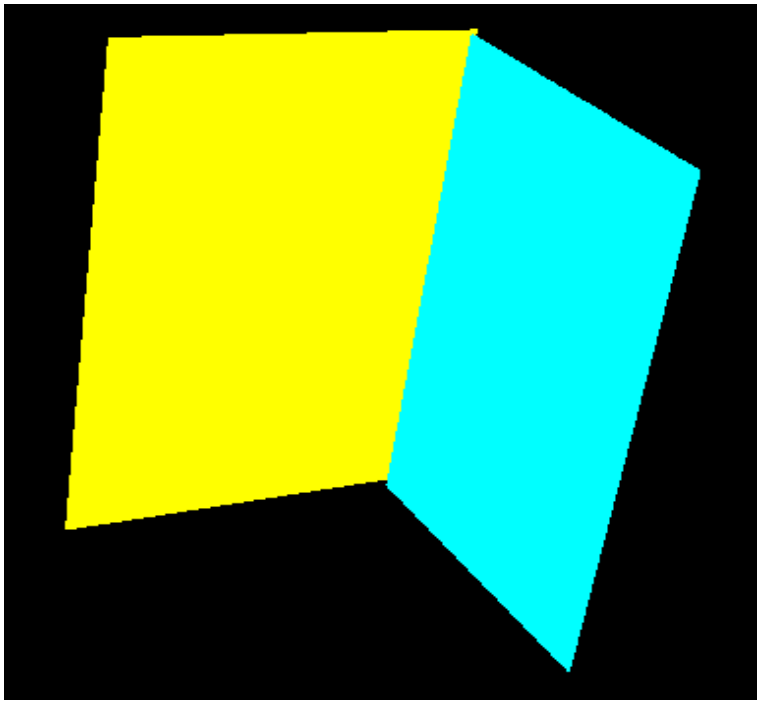
2½-d mapping

Idea:

- Assume **wall-world**: surfaces are vertical planes.
- Create that "3d" representation
- Texture it with the pixel colors ~ *landmarks*.

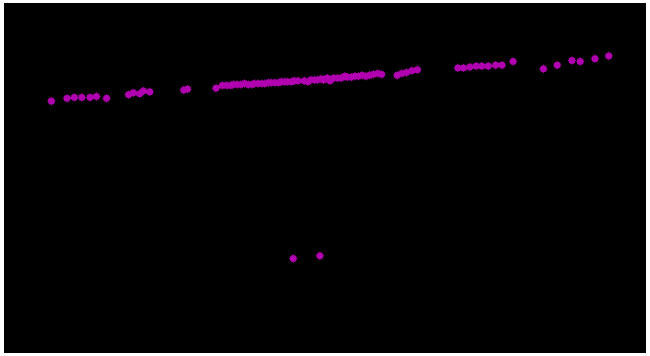


Laser-scan of a corner



Now, as vertical planes

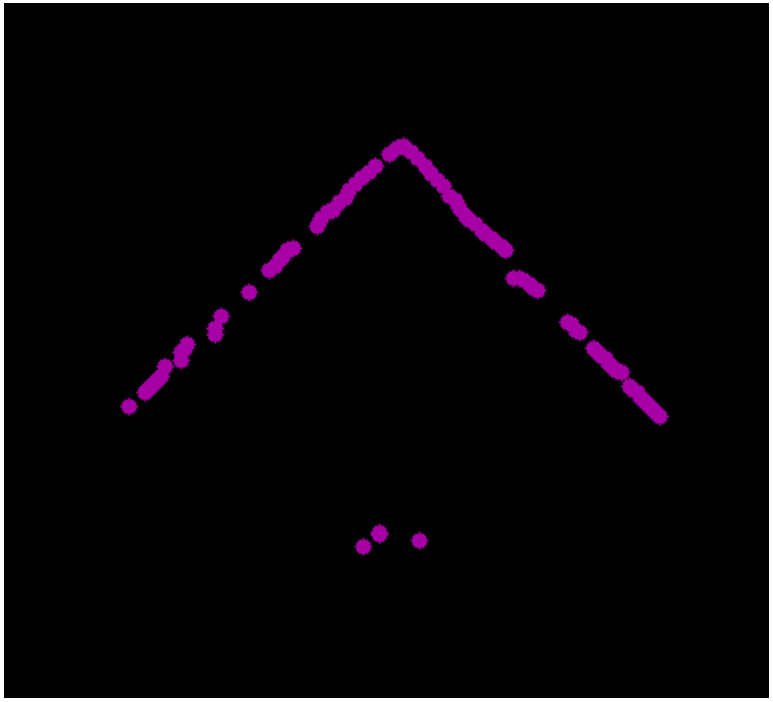
Painting the walls…



Painting the walls…

We can apply any geometry we like ~ here, a cylindrical panorama

Where are the walls?

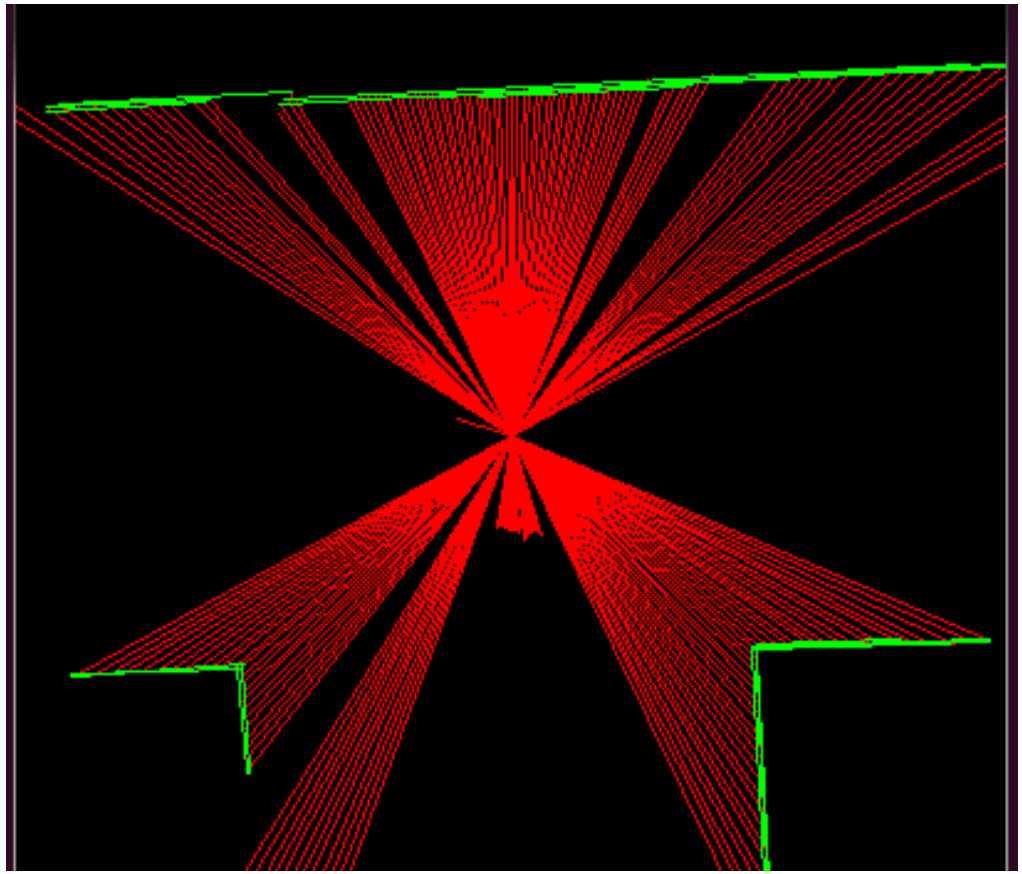


linked to raw_corner_cropped.m4v

Raw laser scans lead to artifacts ~ ***ribbonworld*** vs. wallworld

Finding the walls

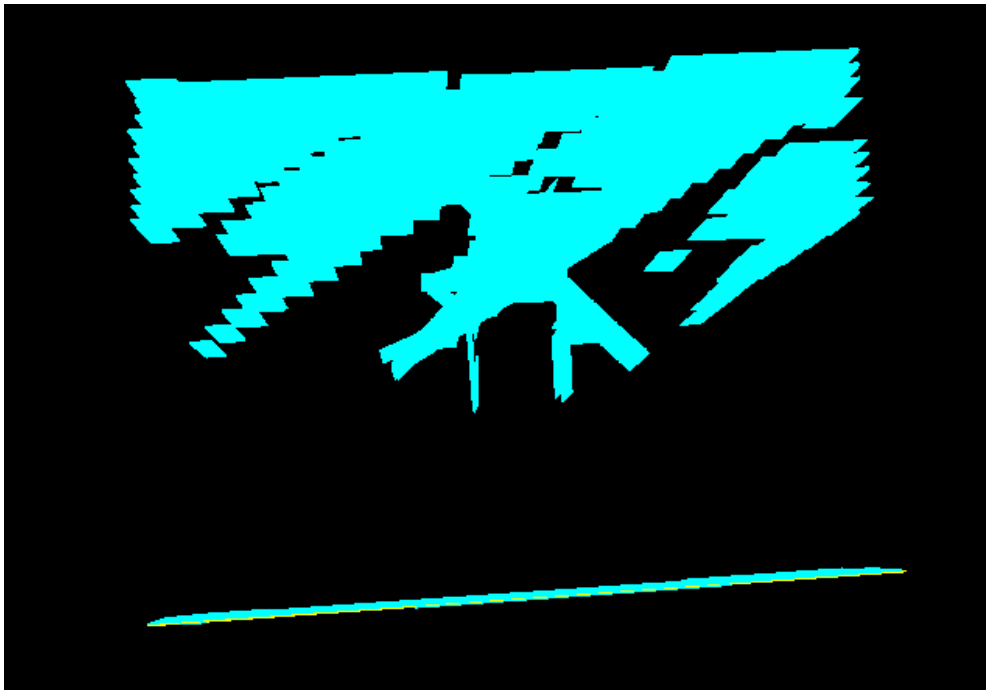
via the Hough transform



~24 lines extracted

Extracting straight lines from laser scans yields *too many* of them

Even worse!



Extracting straight lines from laser scans yields *too many* of them

Selecting the best walls…

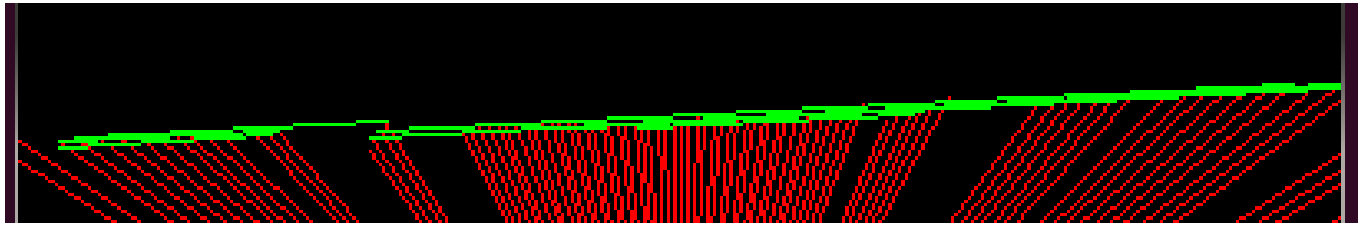
Use the Hough transform to find an initial **set** of wall segments

do

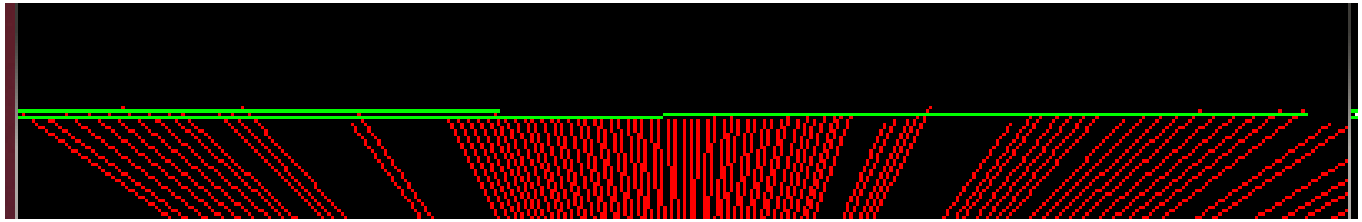
- Compute the slope and position of each segment
- Find a *"close"* pair of segments; remove them from set
- Merge the pair into a single segment and add to set

until no more *"close"* pairs exist.

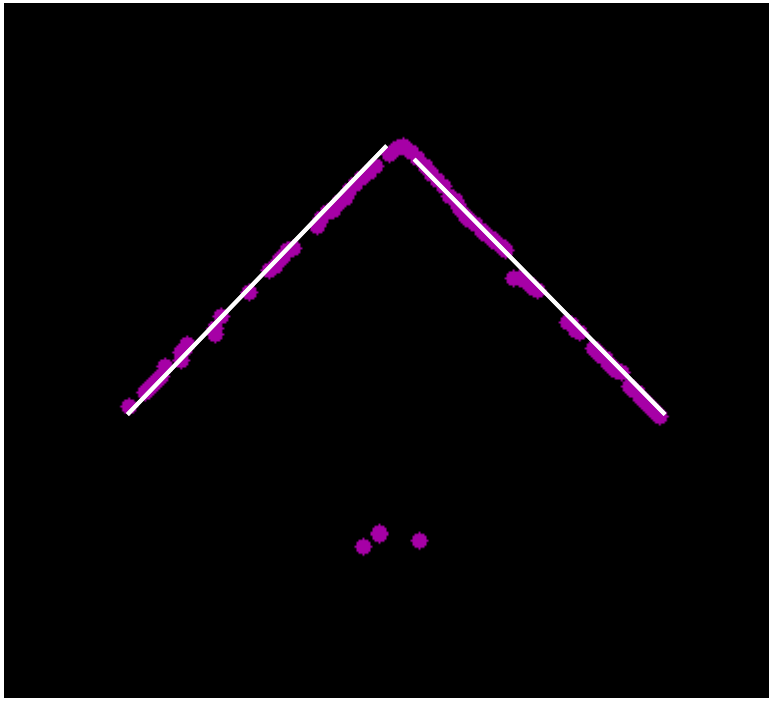
Hough lines



with all but 2 merged



Better!

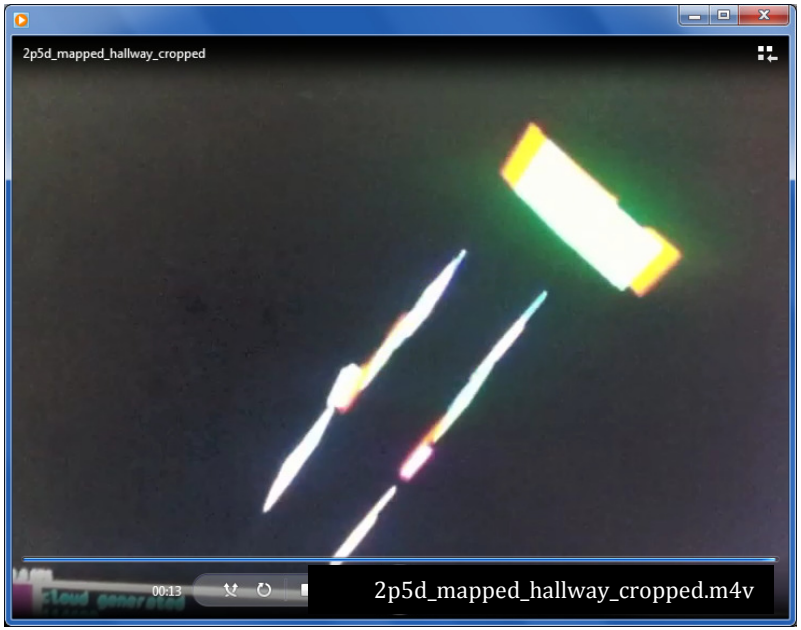


linked to hough_corner_3d_cropped.m4v

First, simplify the 3d structures, *then* paint them …

Building the map…

the robot's final position…



… after creating its 2½-d map

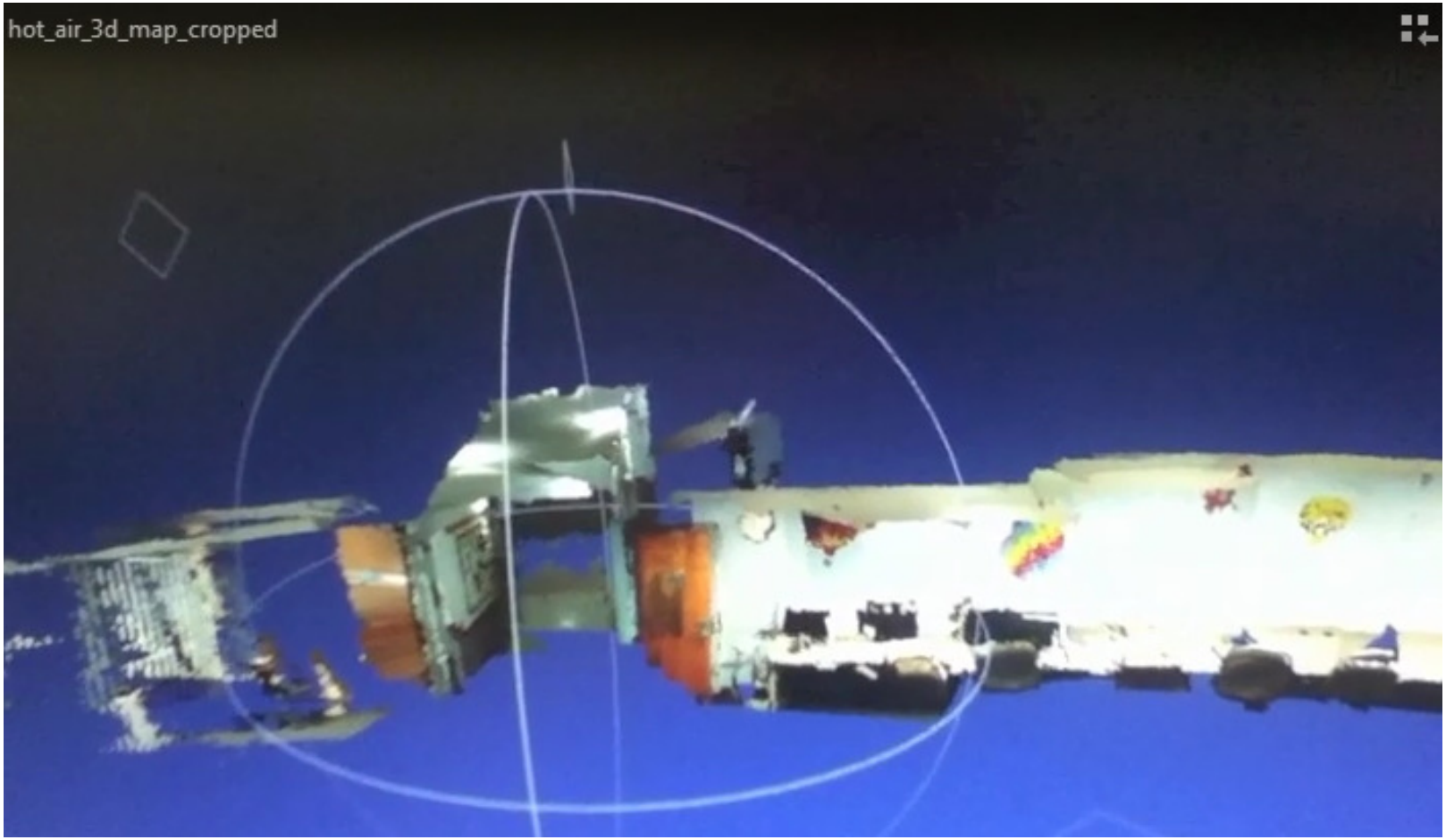
Delegated to 2014: painting these walls in real time…

Or, use the Kinect: *3d mapping*

Demonstration of RGBD-SLAM

SLAM ~ simultaneous localization and mapping

The hot-air lab's map

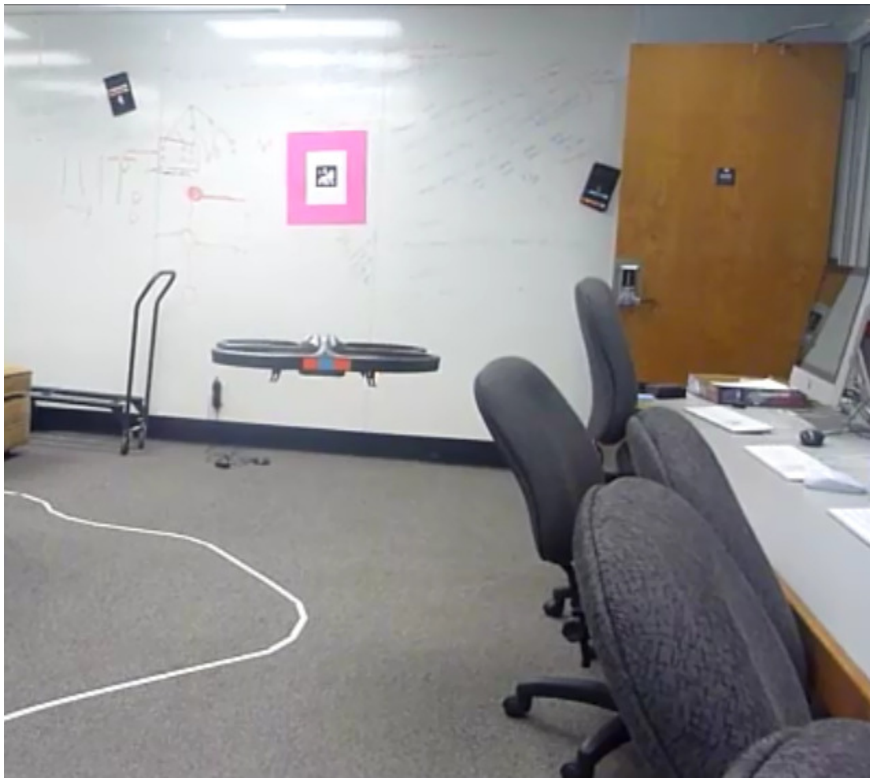


Example of lab and hallway map created by RGBD-SLAM

Two concrete challenges…

more ***robust*** navigation

more ***general*** "lab escape"



bridging 2d sensors with 3d spatial representations

Escape the lab!

Localization-based loop:

(given a known goal)

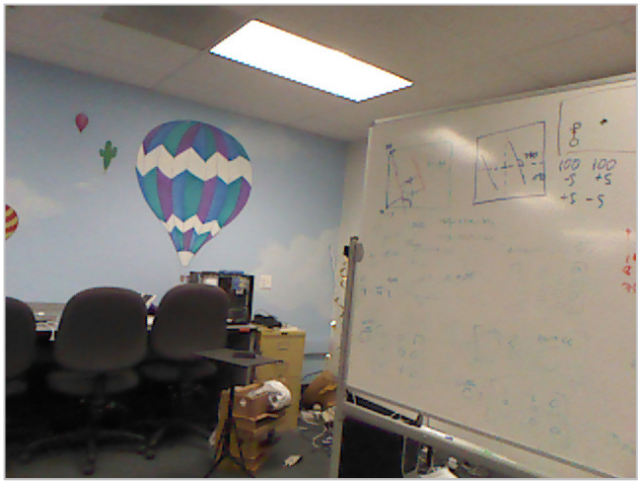
(1) the drone grabs a 2d image

(2) the system ***matches*** that image into the 3d map to locate the drone

(3) once located, the drone computes its desired velocity and ***applies*** it

(4) after two seconds, stop and goto (1)

Image matching?



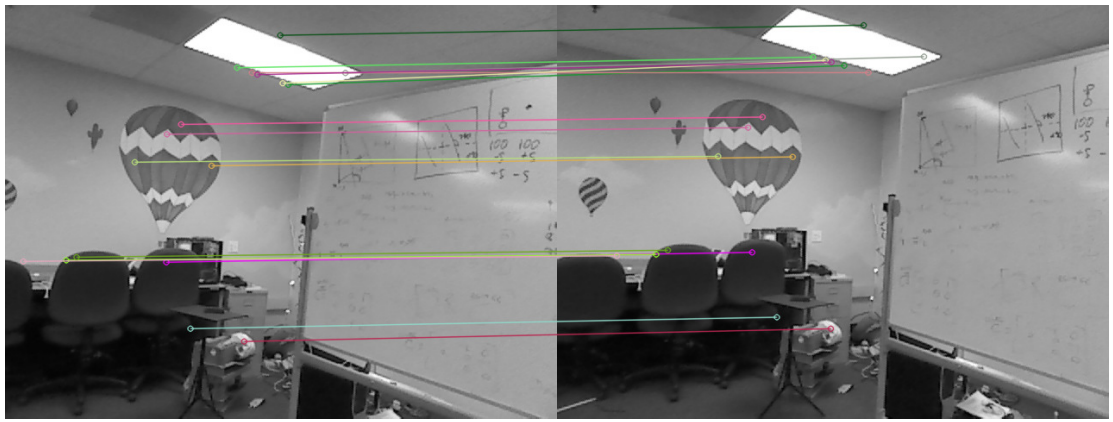
new image (live)

many original images (stored)

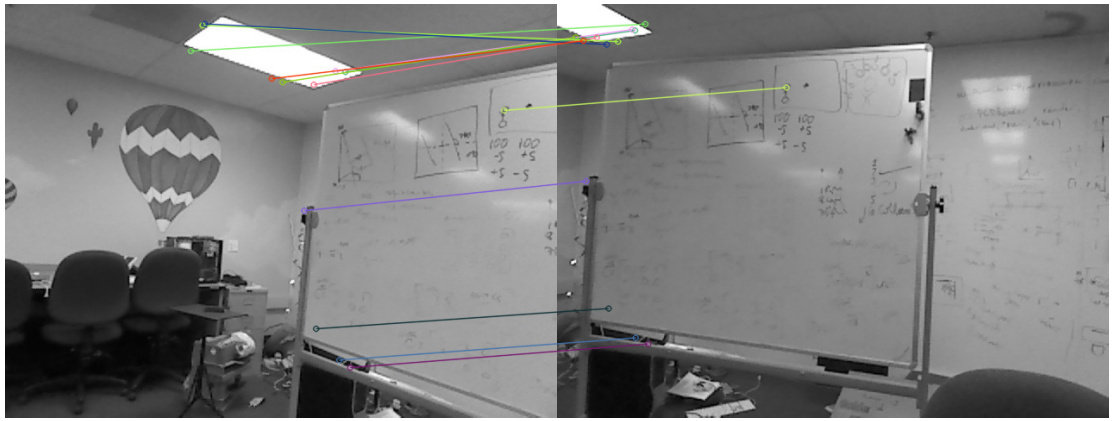
Our approach (well, really Kristina's):

- Find features in each (SIFT)
- Consider all matches (FLANN)
- Ensure bidirectional constraints
- Consistency filtering (homography)
- Best-matching by visual similarity metric
- Tiebreaking by pixel distances

Image matching!



new image (live) | many original images (stored)



1st-best match

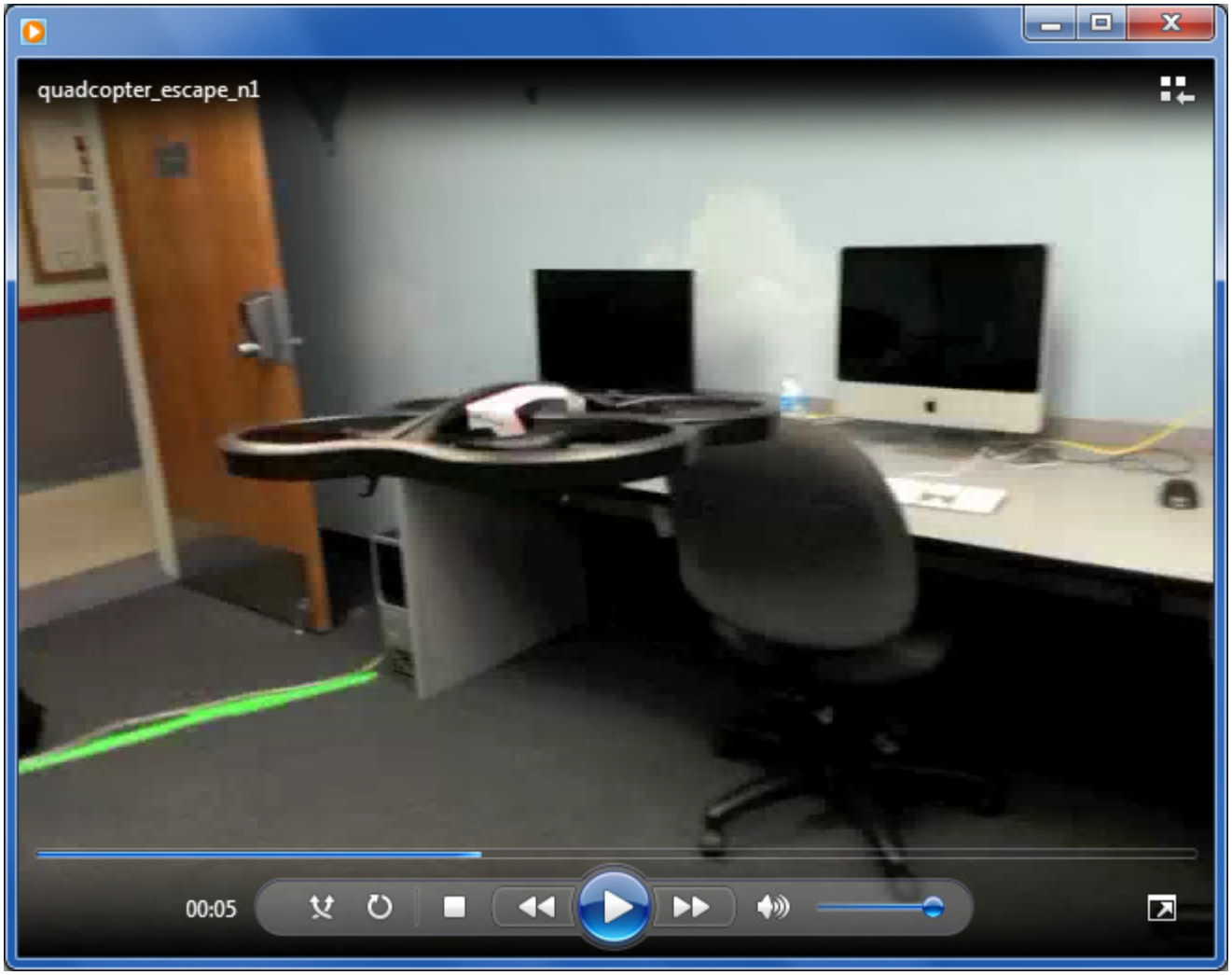
Average feature distance **~ 40 px**

10th-best match

Average feature distance **~ 270 px**

for now, a linear search taking **~10 seconds** for the hot-air map's 42 images

Results



One of the drone's escapes ~ 150 sec.

Details

I will get this stuff…

The 8 successful matches (landmarks) made

Model

I will get this stuff…

A rendering of those 8 estimated positions

Another run

I will get this stuff…

~ 45 seconds

Tradeoffs + realizations

Speed tradeoffs/reasons
Missed matches + handler
Landmark handoffs -
Search-strategy improvements

I will get this stuff...

Skeleton of next summer's robotics agenda...

What about next summer's robots themselves?

New platforms…

LeapMotion

movie of microdrone

movie of lounge chair

Microdrone

"The Sofa"

Thoughts?
Questions?

New platforms…

LeapMotion

movie of microdrone

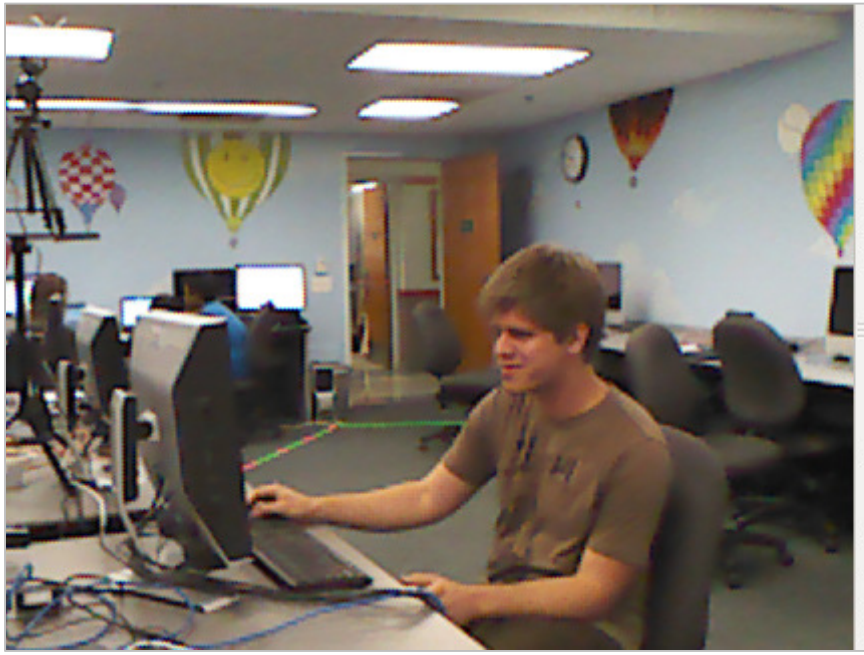
movie of lounge chair

Microdrone

"The Sofa"

Thoughts?
Questions?

Accessing these 3d maps



saves each rgb image

and each depth image

Getting the data: by splicing into the code to extract the input images

Neato *reasoning*

Initial tasks

- learn ASCII API
- write device drivers
- interpret sensor data
- follow corridors
- detect intersections

AI Tasks

- pt-to-pt navigating
- localize and navigate
- minimize ambiguity
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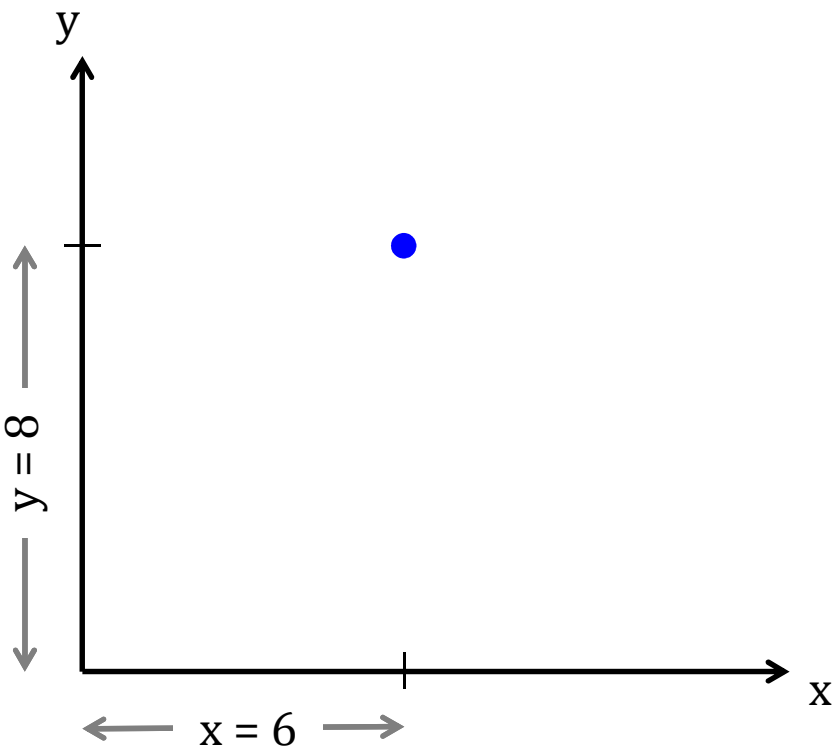
- build 2d and 3d maps

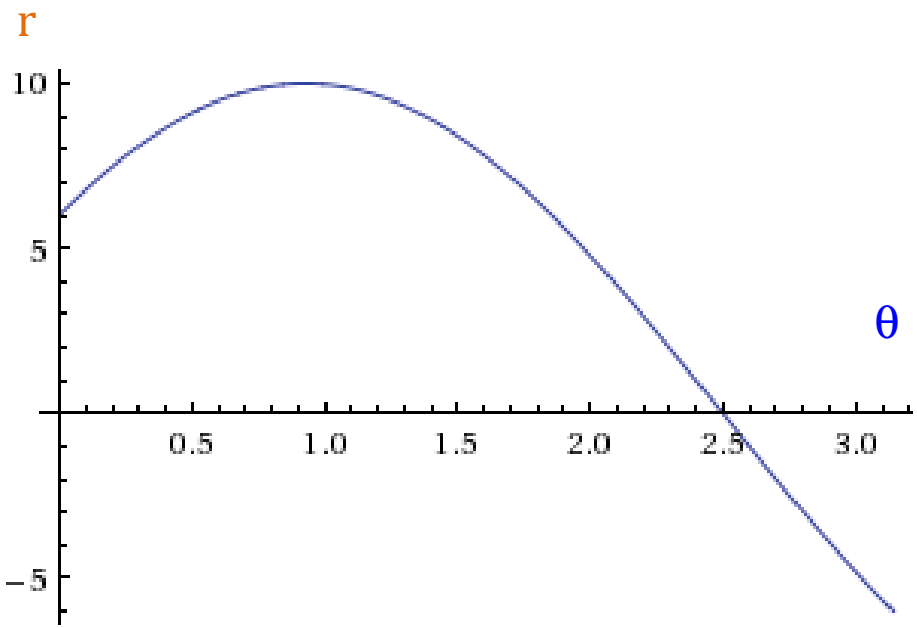
wall placement determines each intersection ***type***

Hough transform

Point space



Line space

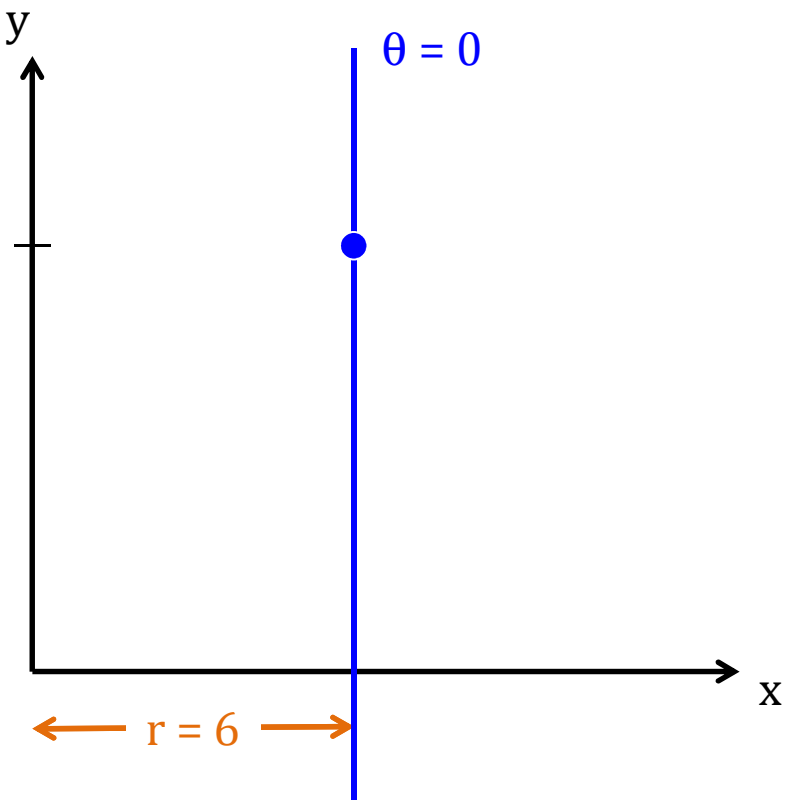


Consider ***one point*** of a laser scan

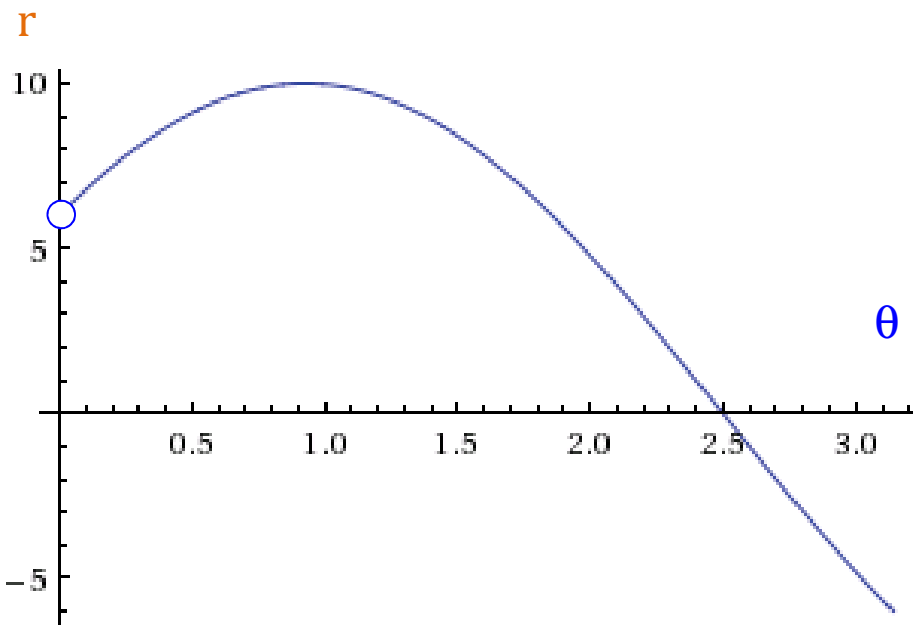
These are ***all*** of the lines through it

Hough transform

Point space



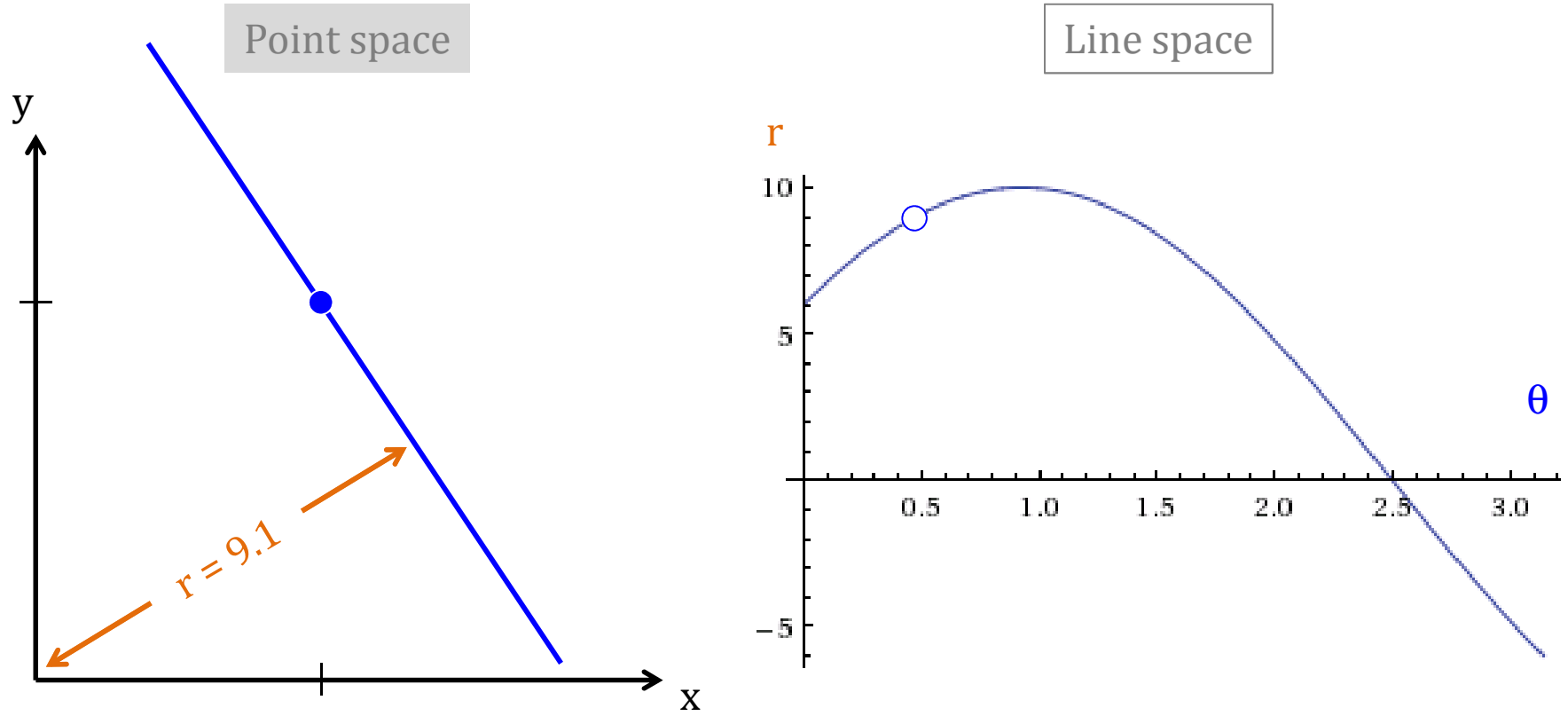
Line space



vertical line ~ θ = 0

The dot is the line r = 6, θ = 0

Hough transform

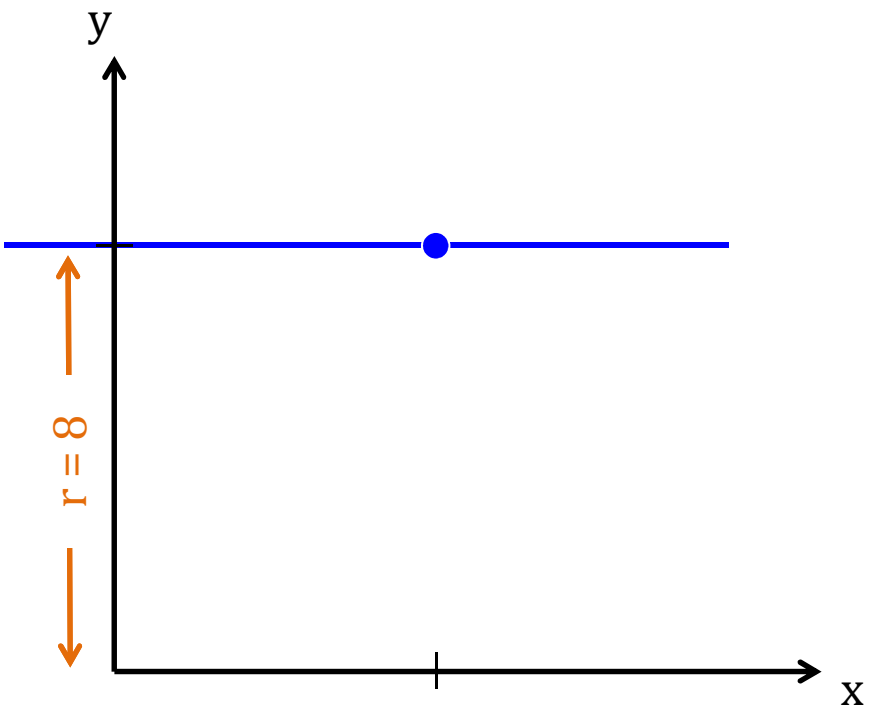


angled line ~ θ = 32°

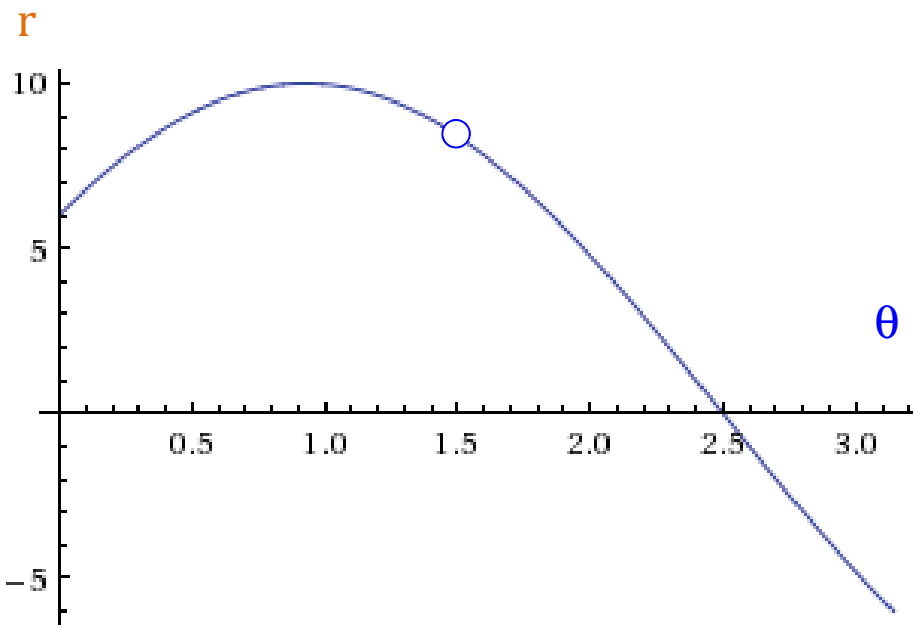
The dot is the line r = 9.1, θ = 32°

Hough transform

Point space



Line space

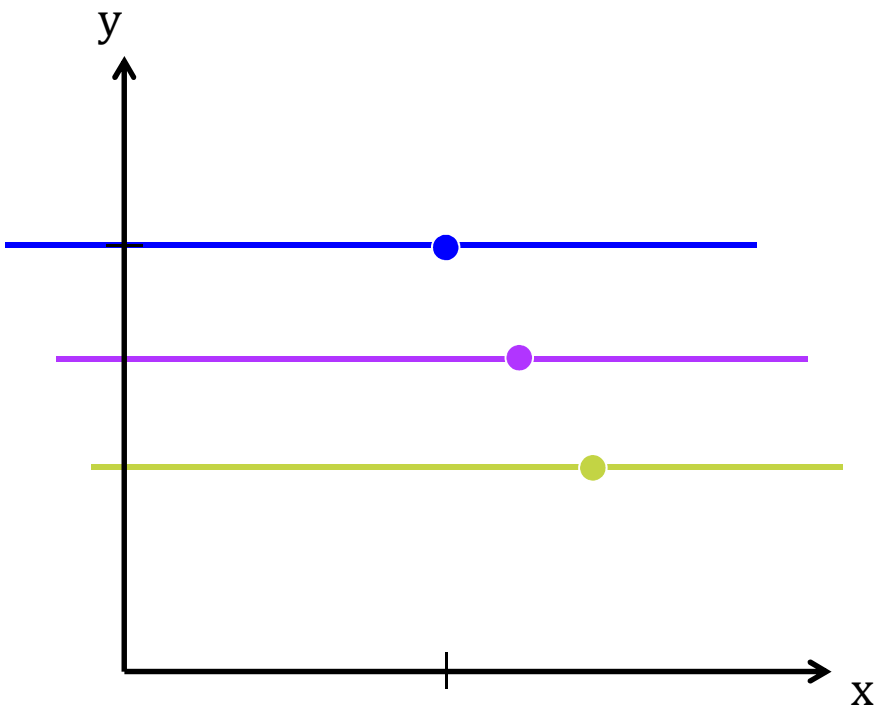


angled line ~ θ = 90°

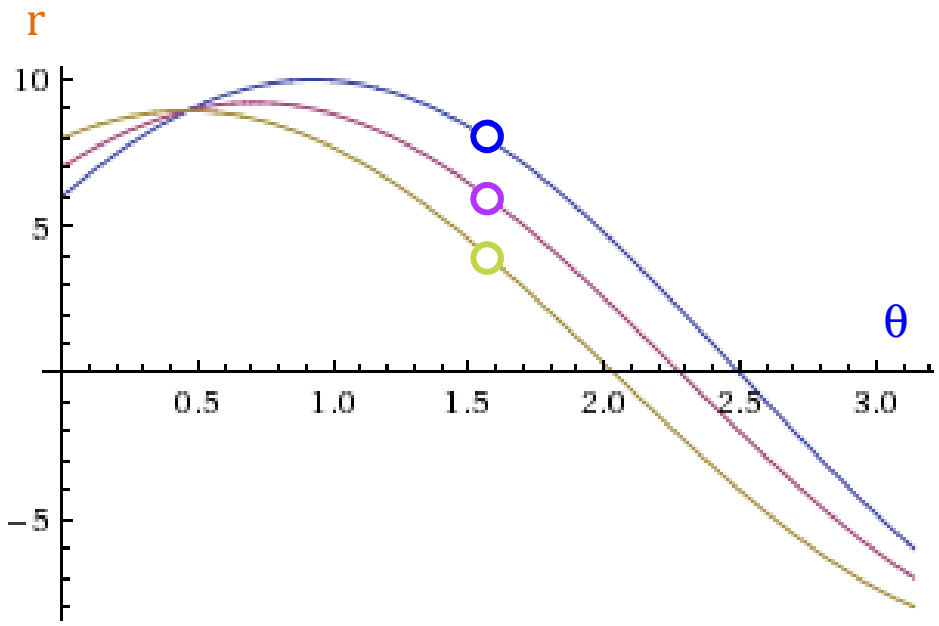
The dot is the line r = 8, θ = 90°

Hough transform

Point space



Line space



three points of a laser scan

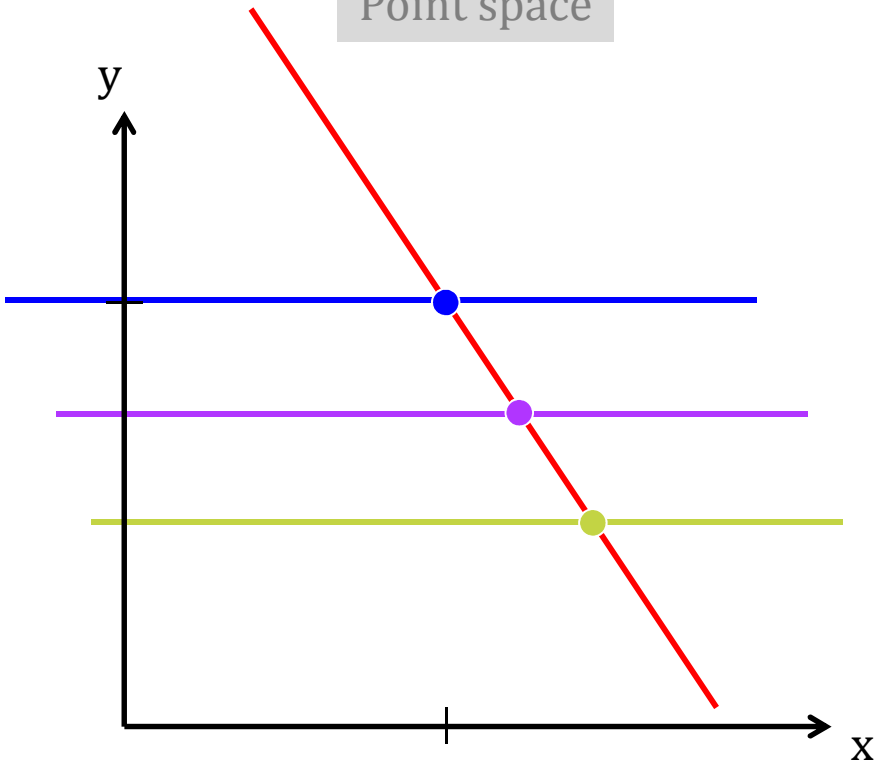
(horizontal lines are shown)

all the lines through all three

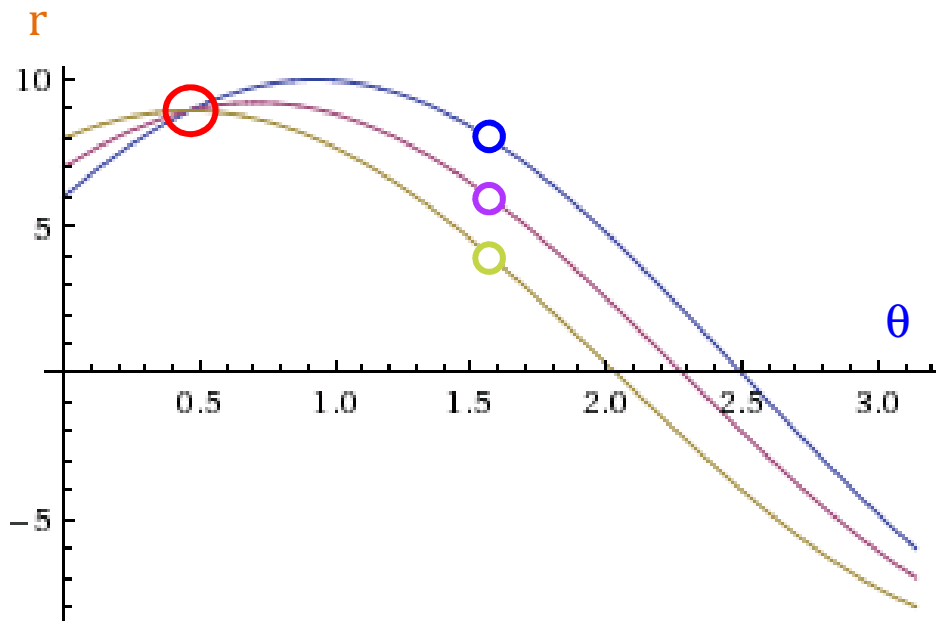
(dots ~ the shown horizontal lines)

Hough transform

Point space



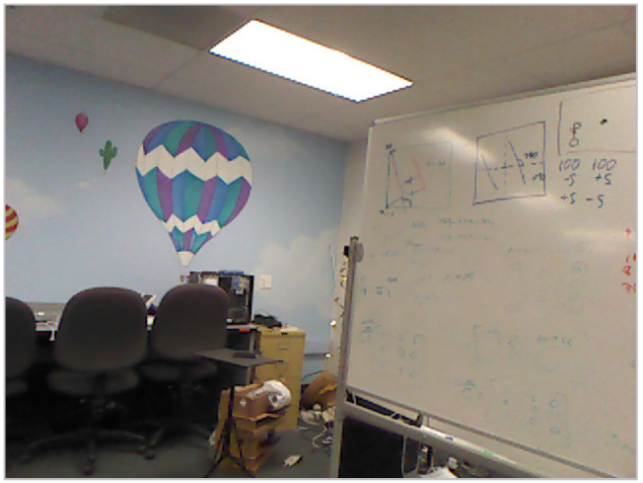
Line space



yield lines with substantial support in the original data

peaks here in line space

Image matching?



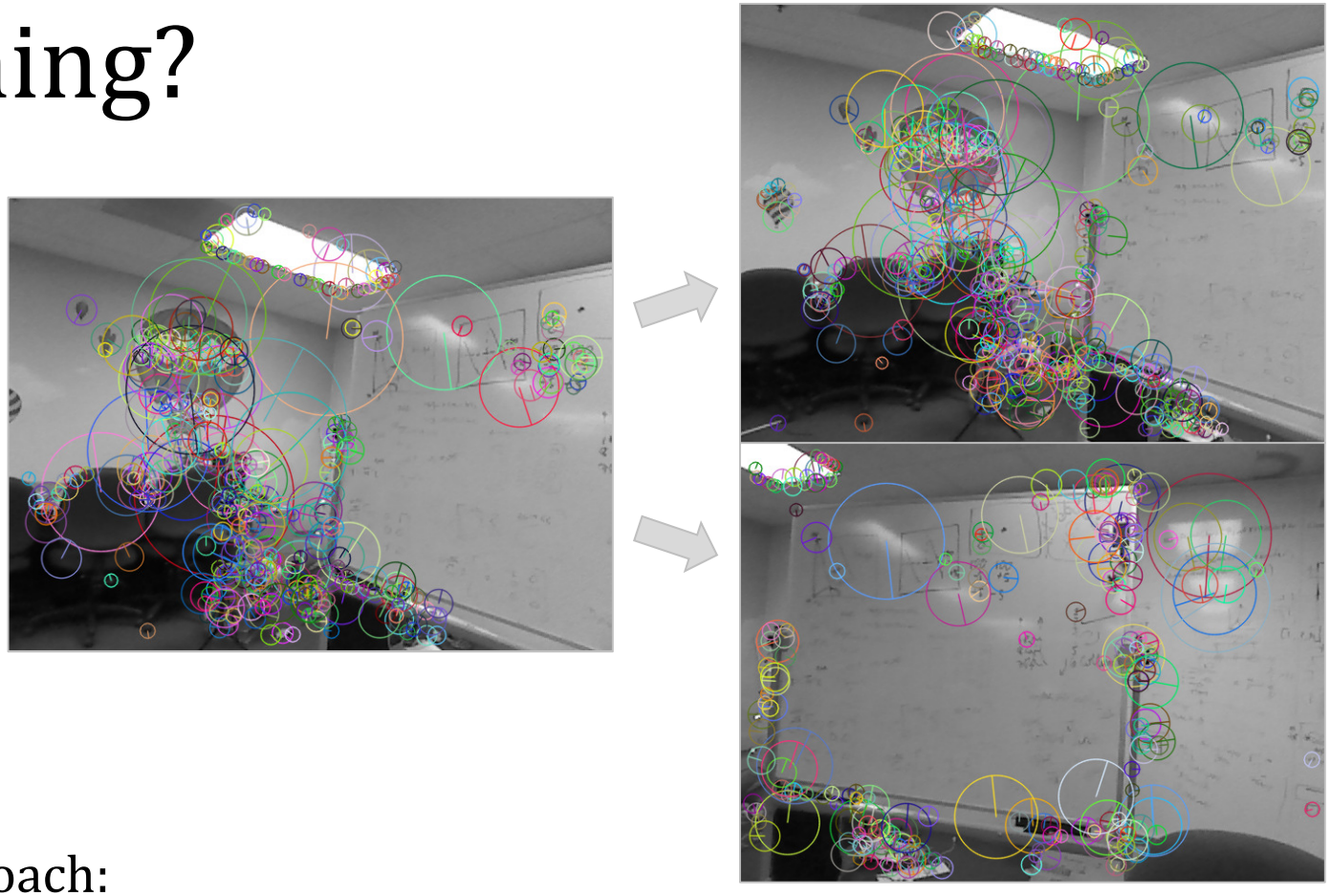
new image

many original images

Our approach:

- Find features in each (SIFT)
- Consider all matches (FLANN)
- Ensure bidirectional constraints
- Consistency filtering (homography)
- Best-matching by visual similarity metric
- Tiebreaking by pixel distances

matching?



Our approach:

- **Find features in each (SIFT)**
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- Ensure bidirectional constraints
- Consistency filtering (homography)
- Best-matching by visual similarity metric
- Tiebreaking by pixel distances

Extract features

Our approach:

- Find features in each (SIFT)
- **Consider all matches (FLANN)**
- Ensure bidirectional constraints
- Consistency filtering (homography)
- Best-matching by visual similarity metric
- Tiebreaking by pixel distances

Nearest-neighbor matching

Our approach:

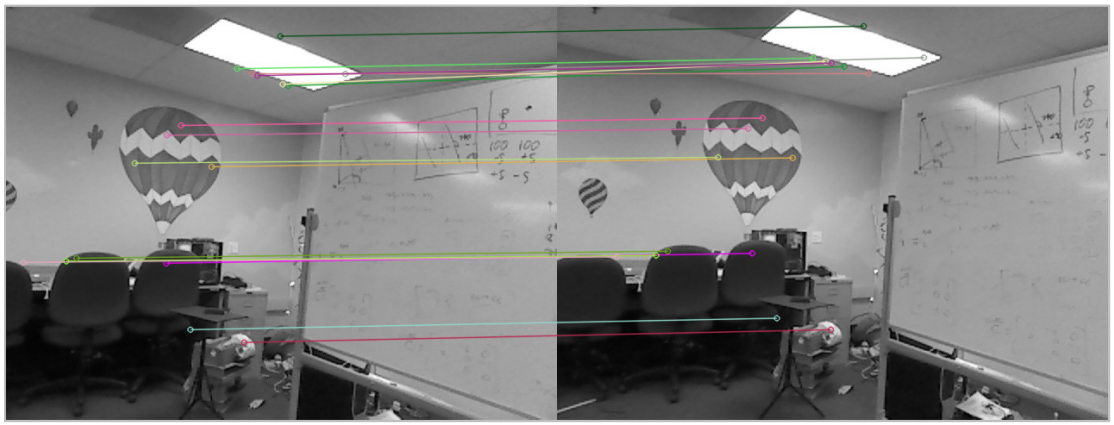
- Find features in each (SIFT)
- Consider all matches (FLANN)
- **Ensure bidirectional constraints**
- Consistency filtering (homography)
- Best-matching by visual similarity metric
- Tiebreaking by pixel distances

Keep only *two-way* best matches

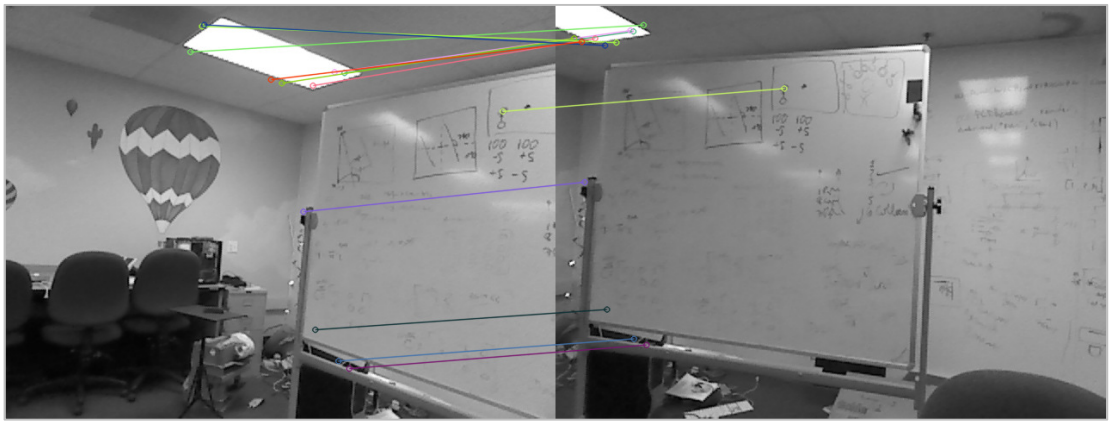
Our approach:

- Find features in each (SIFT)
- Consider all matches (FLANN)
- Ensure bidirectional constraints
- **Consistency filtering (via homography)**
- Best-matching by visual similarity metric
- Tiebreaking by pixel distances

Keep *geometrically realistic* matches



1st-best match

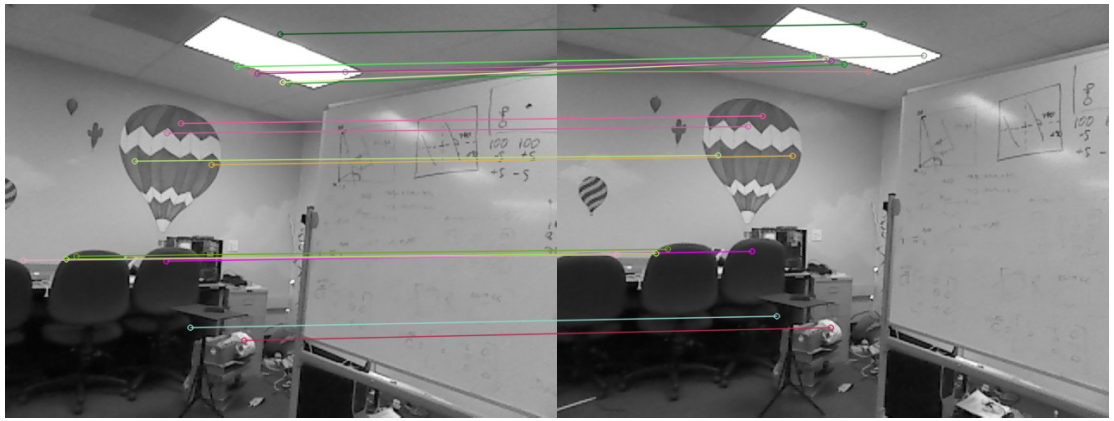


10th-best match

Our approach:

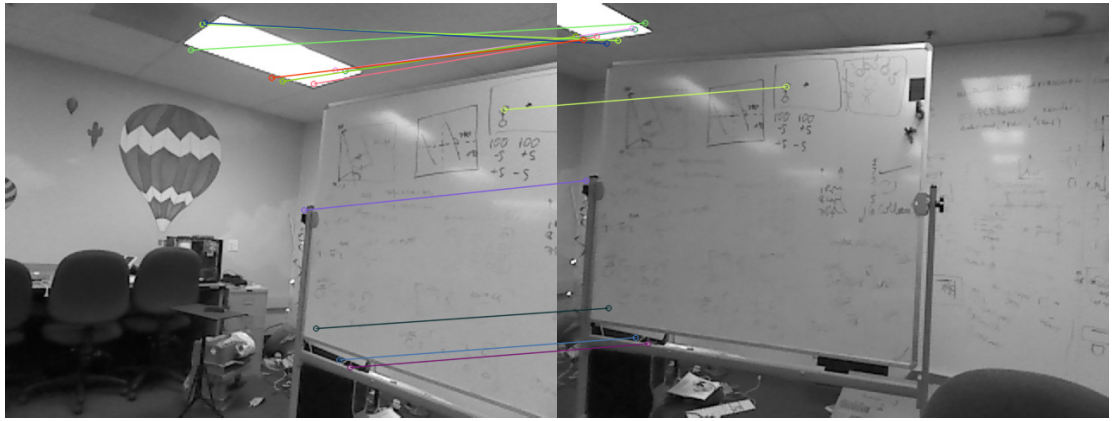
- Find features in each (SIFT)
- Consider all matches (FLANN)
- Ensure bidirectional constraints
- Consistency filtering (via homography)
- **Best-matching by visual similarity metric**
- Tiebreaking by pixel distances

Visual “closeness”



1st-best match

Average feature distance **~ 40 px**



10th-best match

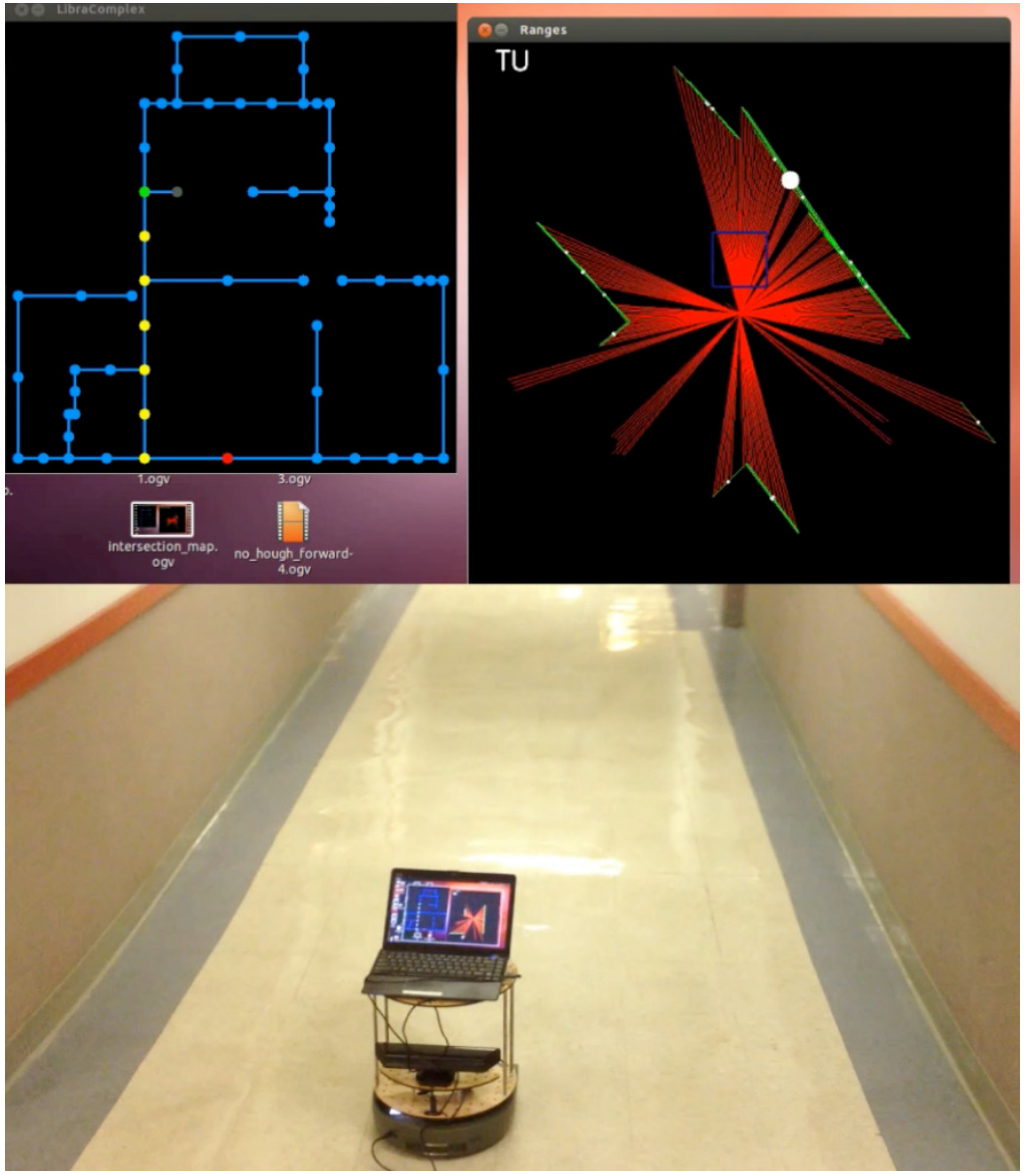
Average feature distance **~ 270 px**

Our approach:

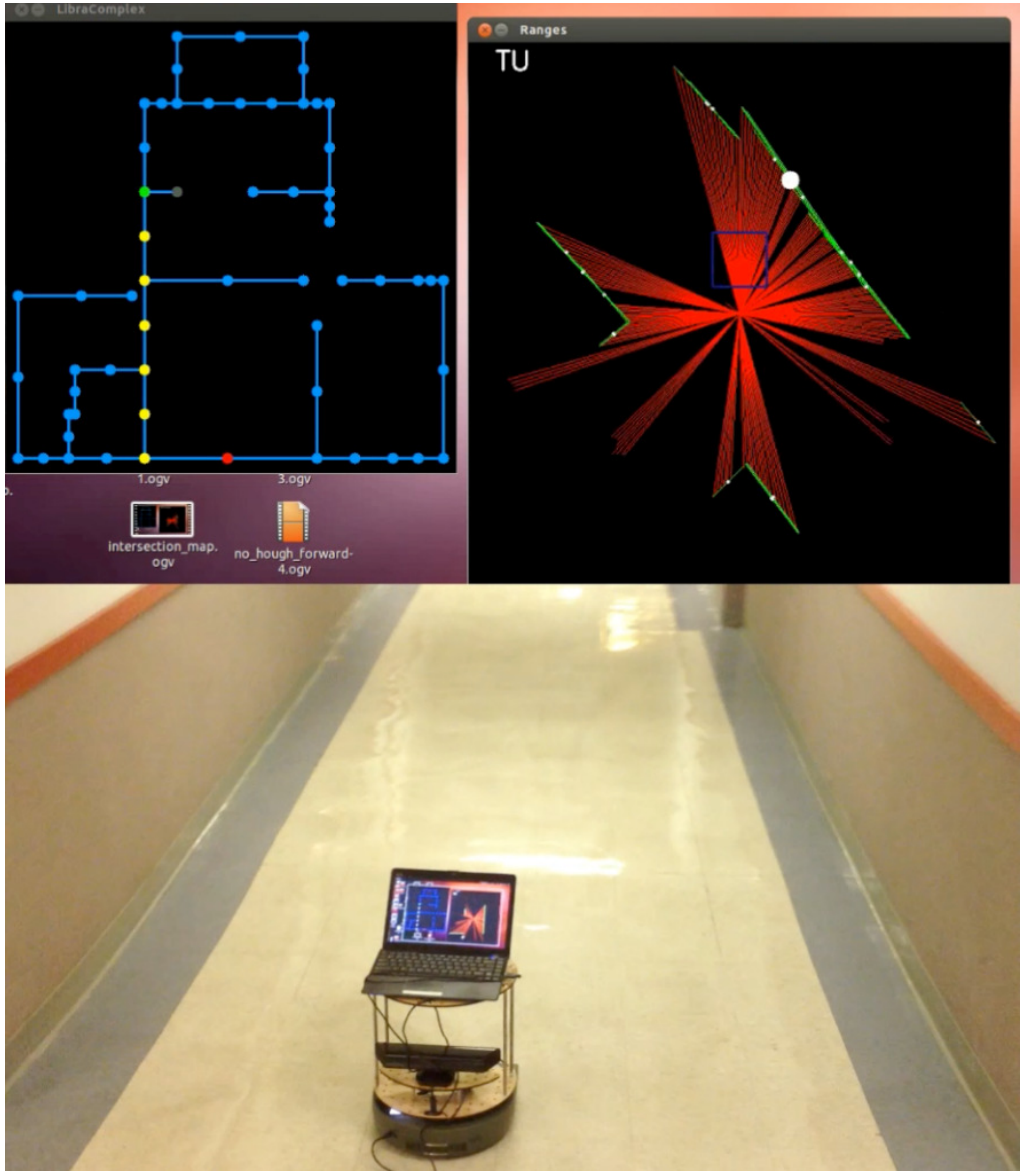
- Find features in each (SIFT)
- Consider all matches (FLANN)
- Ensure bidirectional constraints
- Consistency filtering (via homography)
- Best-matching by visual similarity metric
- **Tiebreaking by pixel distances**

Pixel "closeness"

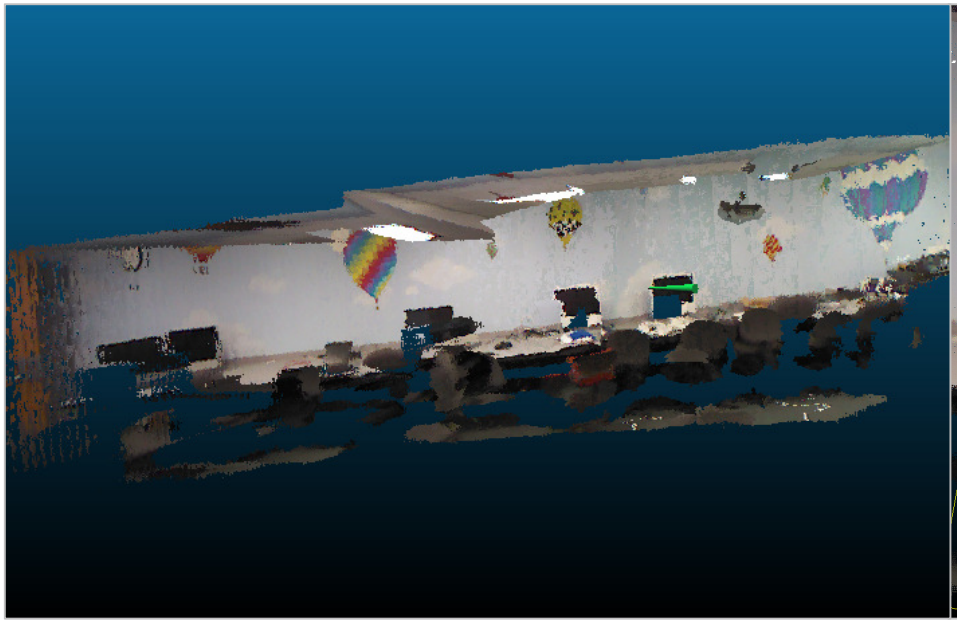
Map-based navigation…



Next: localization



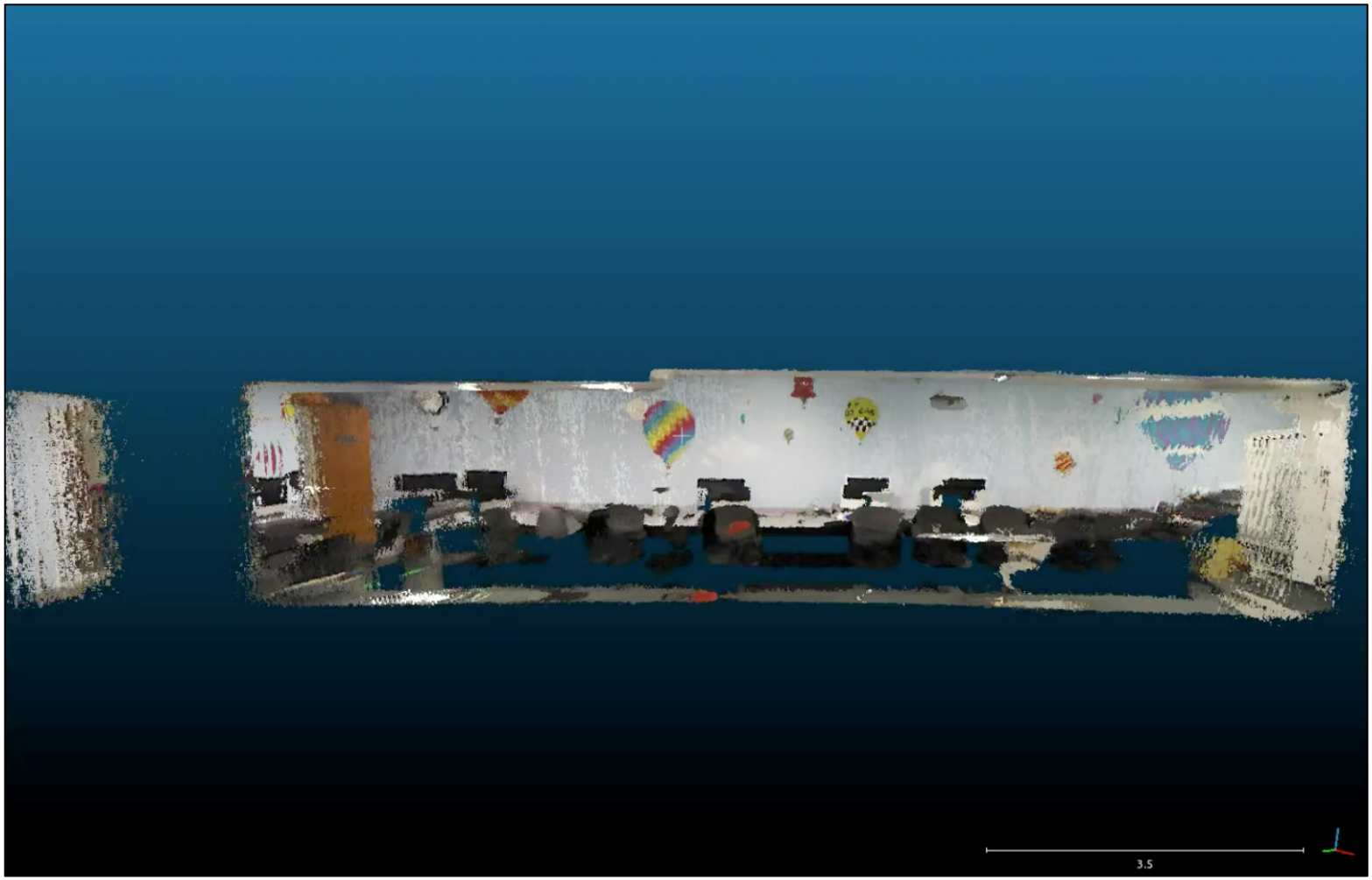
Accessing these models



3d lab model ~ with a surface added

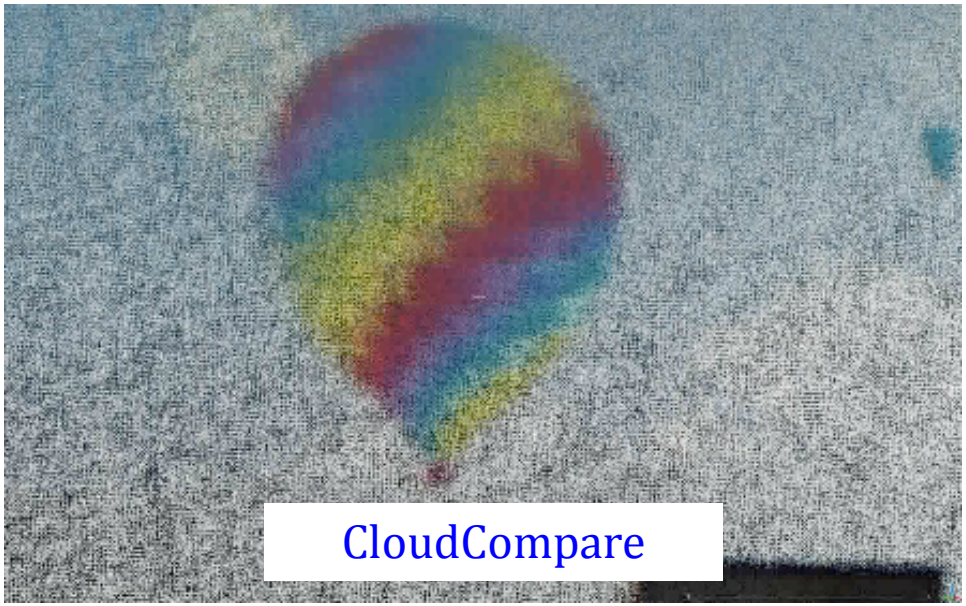
the rendered view from that green cone

Accessing these models



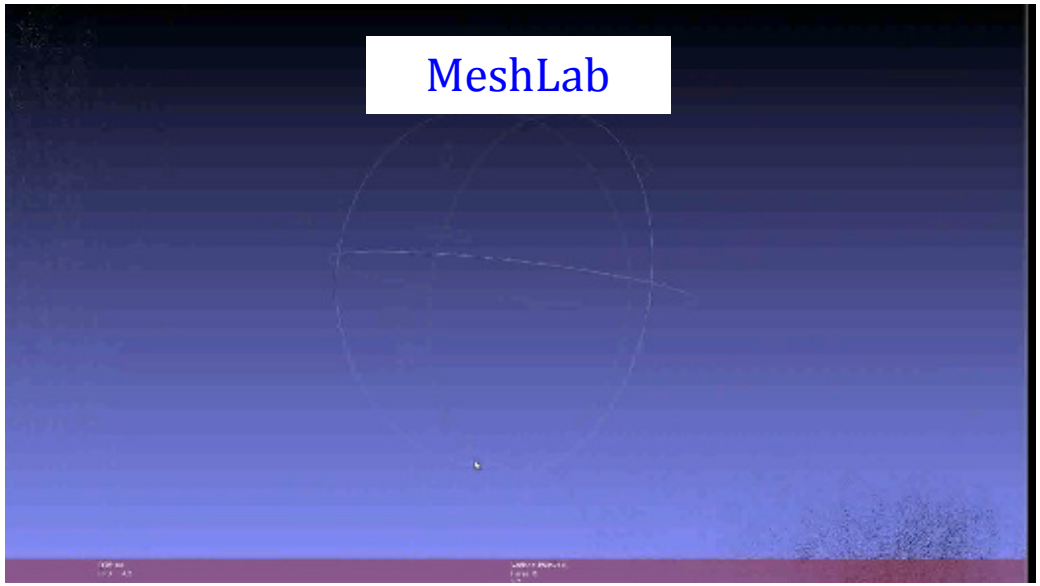
Cloud Compare is a visualizer that can include our own “annotations” …

Zooming vs. Moving



zooming in to the balloon…

… vs. moving towards/past it



Using these models

How might a robot with an ordinary camera, i.e., only 2d sensing, use these 3d models?

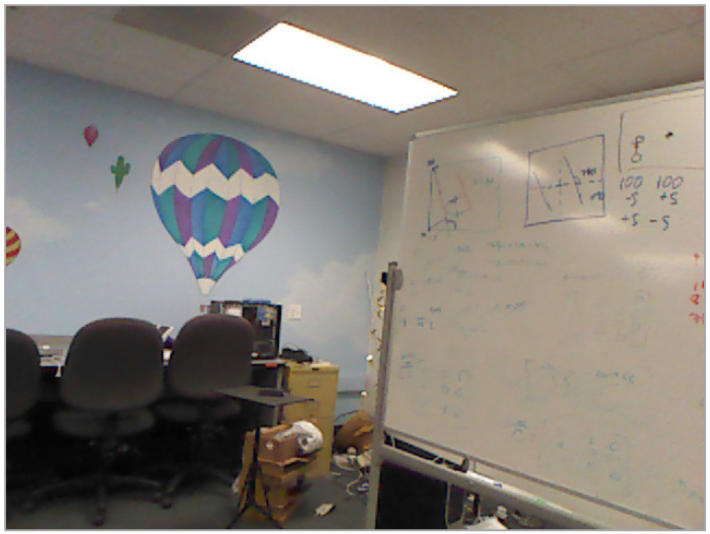
2d – 2d matching

3d – 3d matching

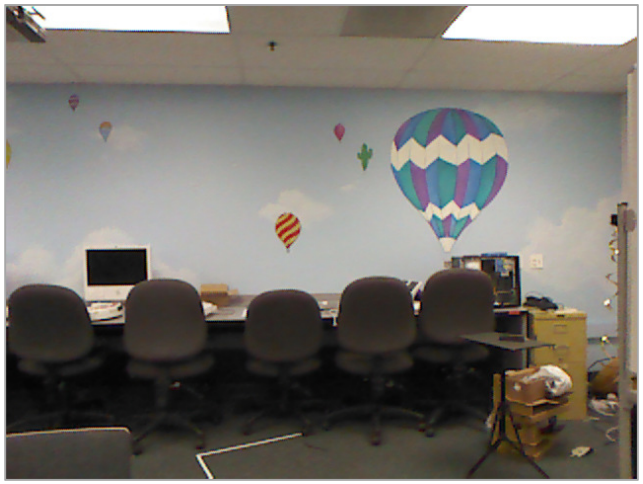
Ideally, a 2d sensing system could localize – *and reason* – within a 3d model

2d – 2d matching

with a **new image** from a robot (or other device)



we could compare



vs. original images

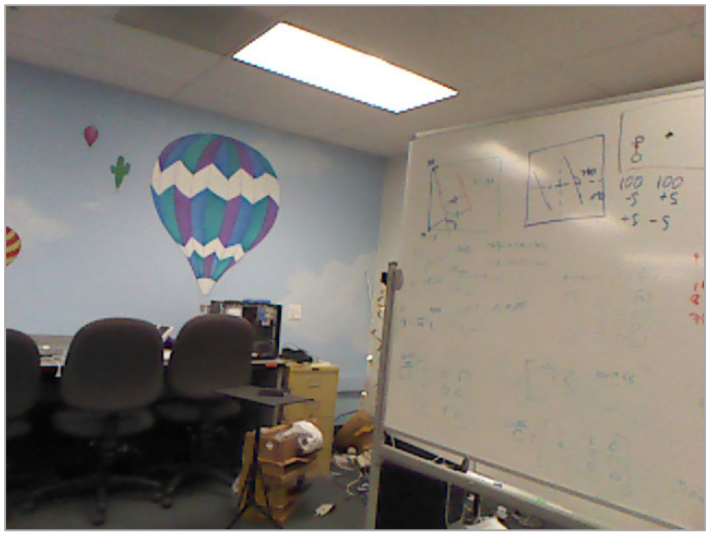
These are the images used to create the 3d model in the first place: fewer, higher-fidelity.

vs. rendered images

Images yielded by the 3d model: arbitrarily many, but lower-quality.

2d – 2d matching

with a **new image** from a robot (or other device)



we could compare

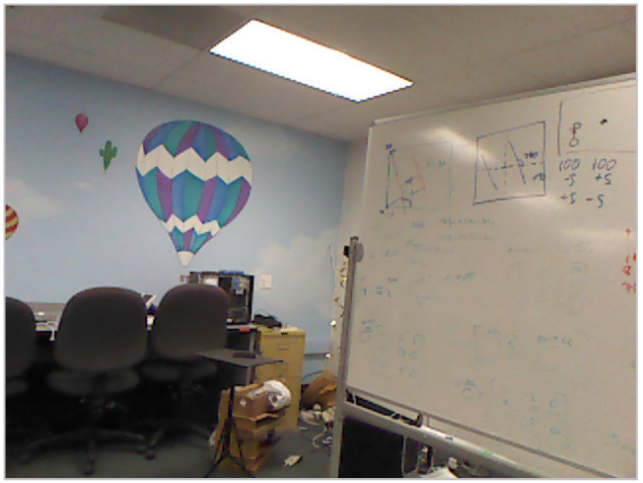
vs. original images

These are the images used to create the 3d model in the first place: fewer, higher-fidelity.

vs. rendered images

Images yielded by the 3d model: arbitrarily many, but lower-quality.

Matching?



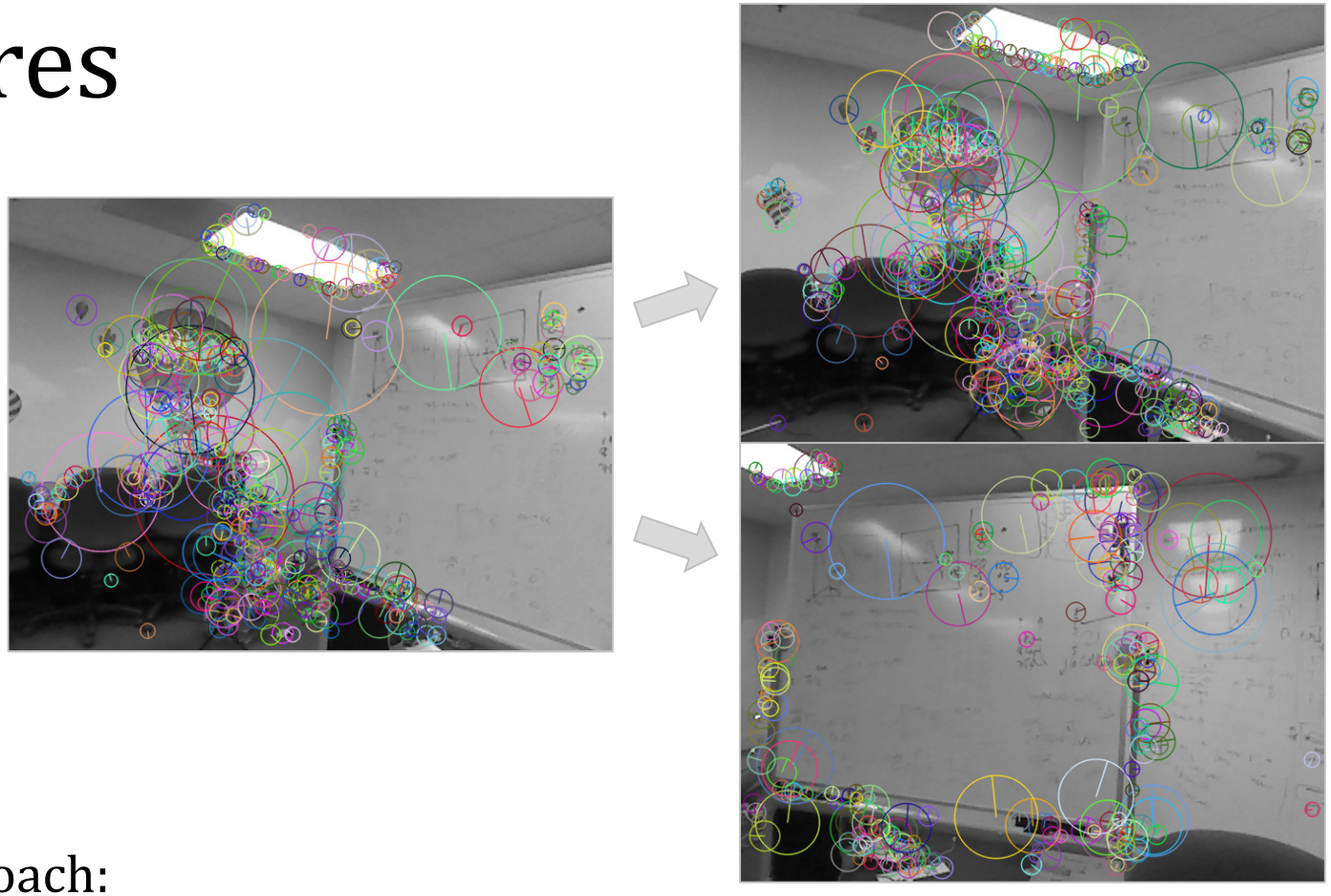
new image

many original images

Our approach:

- Find features in each (SIFT)
- Consider all matches (FLANN)
- Ensure bidirectional constraints
- Consistency filtering (homography)
- Best-matching by visual similarity metric
- Tiebreaking by pixel distances

Features



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Nearest-neighbor matching

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Keep only *two-way* best matches

Our approach:

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- Ensure bidirectional constraints
- **Consistency filtering (via homography)**
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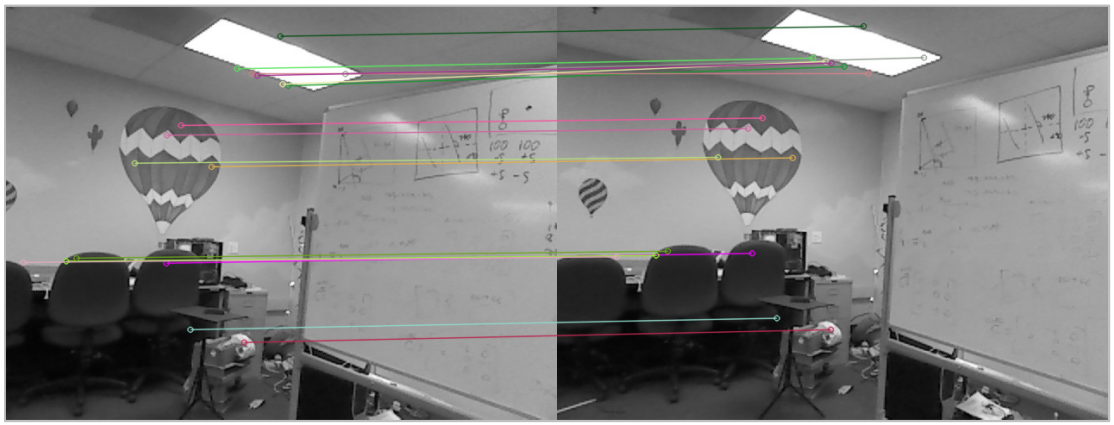
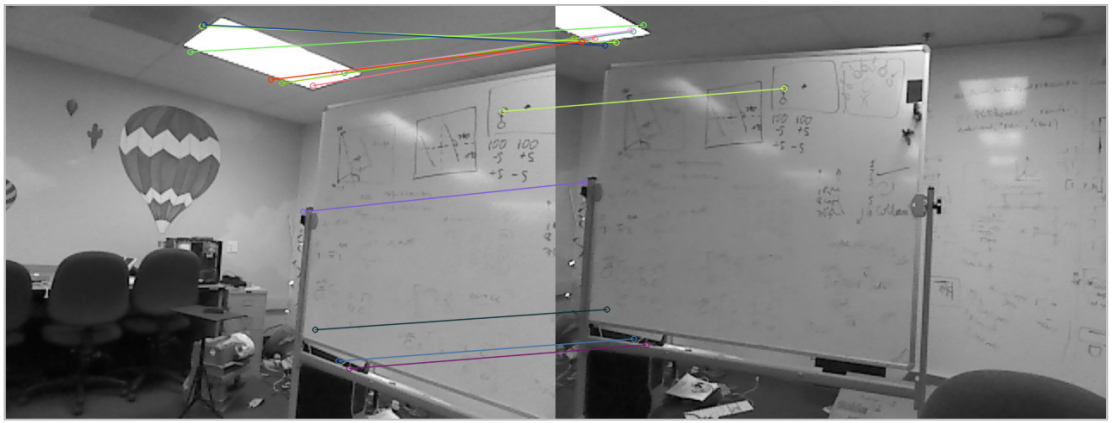
- Tiebreaking by pixel distances

Keep *geometrically realistic* matches



1st-best match



10th-best match

Our approach:

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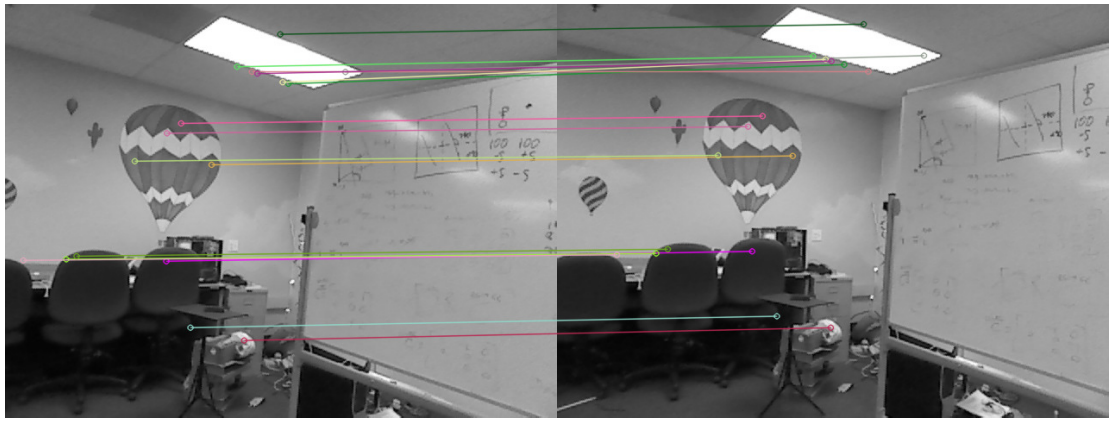
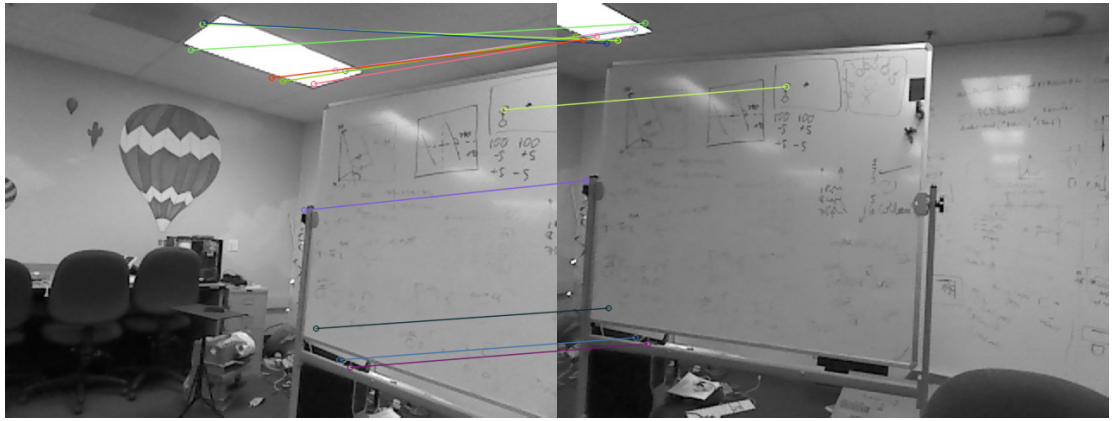
- Ensure bidirectional constraints
- Consistency filtering (via homography)
- **Best-matching by visual similarity metric**
- Tiebreaking by pixel distances

Visual “closeness”



1st-best match

Average feature distance **~ 40 px**



10th-best match

Average feature distance **~ 270 px**

Our approach:

- Find features in each (SIFT)
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- Ensure bidirectional constraints
- Consistency filtering (via homography)
- Best-matching by visual similarity metric
- **Tiebreaking by pixel distances**

Pixel “closeness”

PCL: Point Cloud Library

pcl About News Blog Downloads

Documentation

How to extract NARF keypoint from a range image

This tutorial demonstrates how to extract NARF key points from a range image. The executable enables us to load a point cloud from disc (or create it if not gi
both in an image and a 3D viewer.

The code

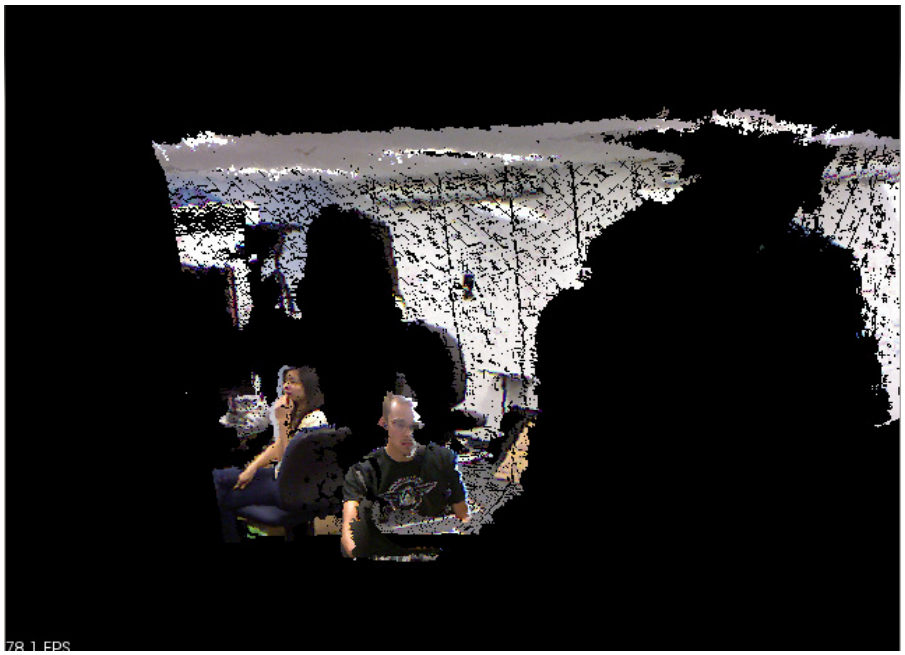
First, create a file called, let's say, `narf_keypoint_extraction.cpp` in your favorite editor, and place the following code inside it:

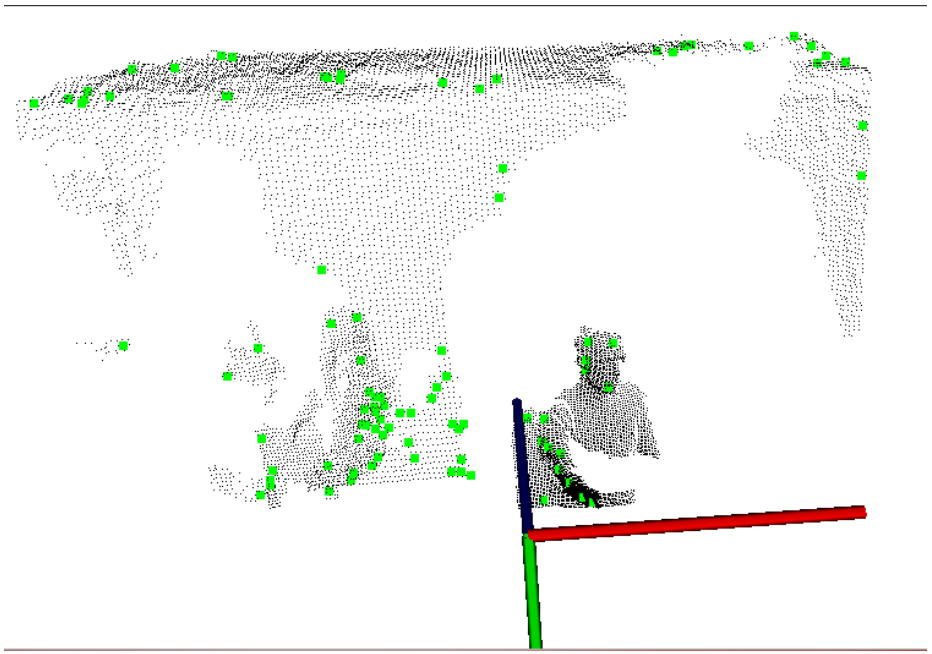
```
/* \author Bastian Steder */

#include <iostream>

#include <boost/thread/thread.hpp>
#include <pcl/range_image/range_image.h>
#include <pcl/io/pcd_io.h>
#include <pcl/visualization/range_image_visualizer.h>
#include <pcl/visualization/pcl_visualizer.h>
#include <pcl/features/range_image_border_extractor.h>
#include <pcl/keypoints/narf_keypoint.h>
#include <pcl/console/parse.h>

typedef pcl::PointXYZ PointType;

// --------------------
// -----Parameters-----
// --------------------
float angular_resolution = 0.5f;
float support_size = 0.2f;
pcl::RangeImage::CoordinateFrame coordinate_frame = pcl::RangeImage::CAMERA_FRAME;
bool setUnseenToMaxRange = false;

// --------------
// -----Help-----
// --------------
void
printUsage (const char* progName)
{
  std::cout << "\n\nUsage: "<<progName<<" [options] <scene.pcd>\n\n"
            << "Options:\n"
            << "-------------------------------------------\n"
            << "-r <float>   angular resolution in degrees (default "<<angular_resolution<<")\n"
            << "-c <int>     coordinate frame (default "<< (int)coordinate_frame<<")\n"
            << "-m           Treat all unseen points as maximum range readings\n"
            << "-s <float>   support size for the interest points (diameter of the used sphere - "
            <<                                                    "default "<<support_size<<")\n"
```

- 3D-Reasoning
- Easy point cloud access

NARFs!

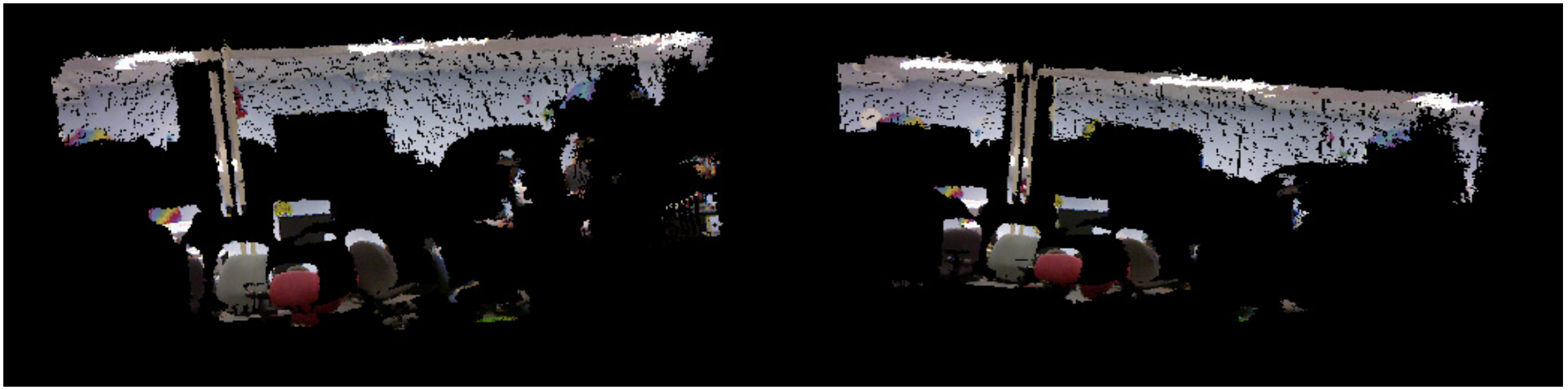
3d features: *Normal Aligned Radial Features*





- NARF features are purely based on the ***range image*** of a point cloud: its geometry, not its looks (SIFT)
- They are based on the normals of the point cloud's surfaces
- They are places distinguishable from multiple perspectives.

3d matching

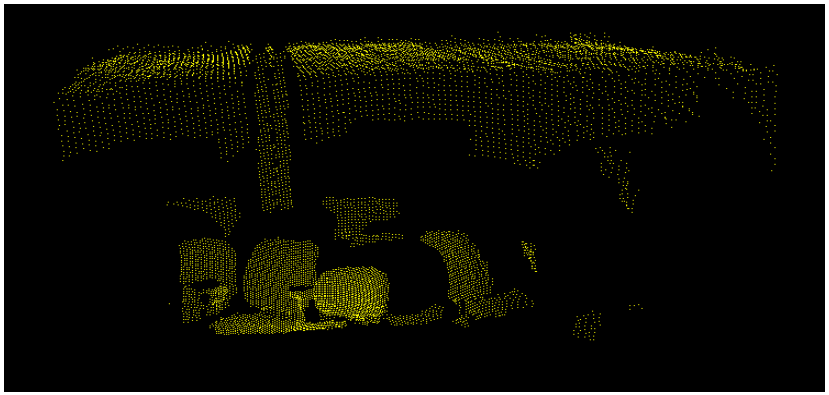


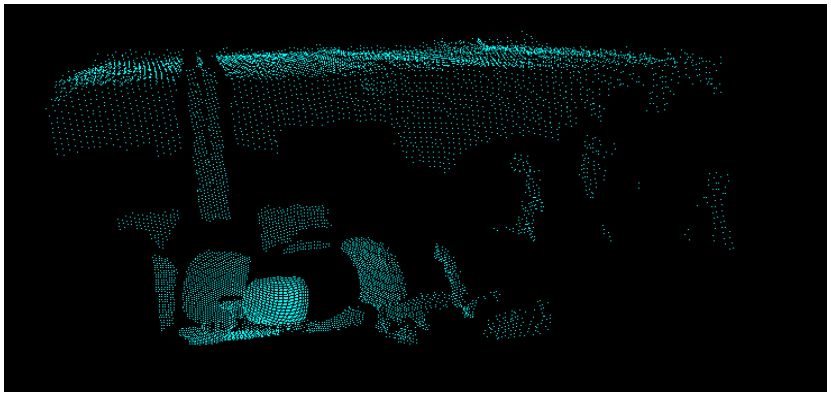
- Take two point clouds
- Find NARFs
- Match features and find transform
- Make transform and combine

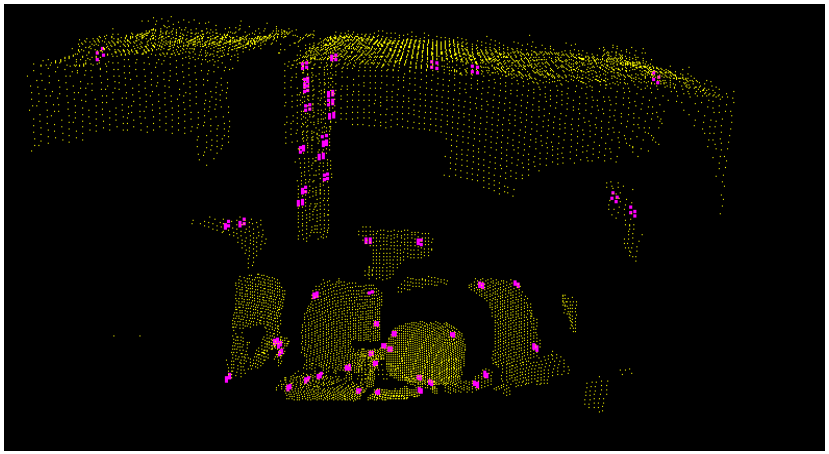
naive merging

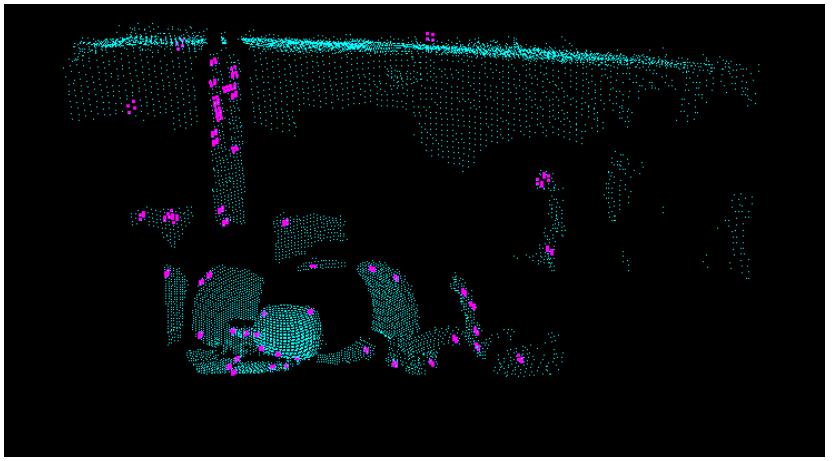
3d SLAM

Simultaneous Localization And Mapping





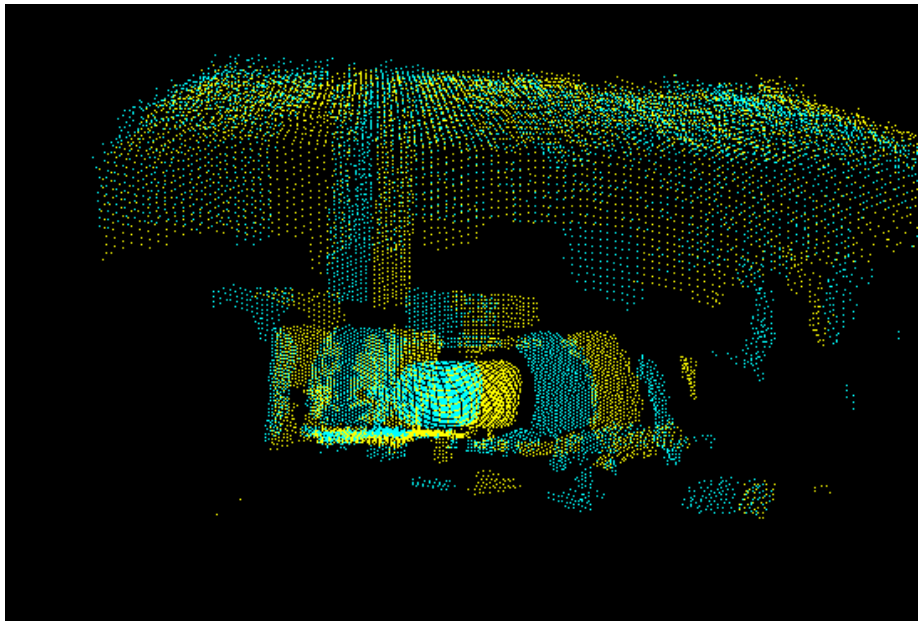


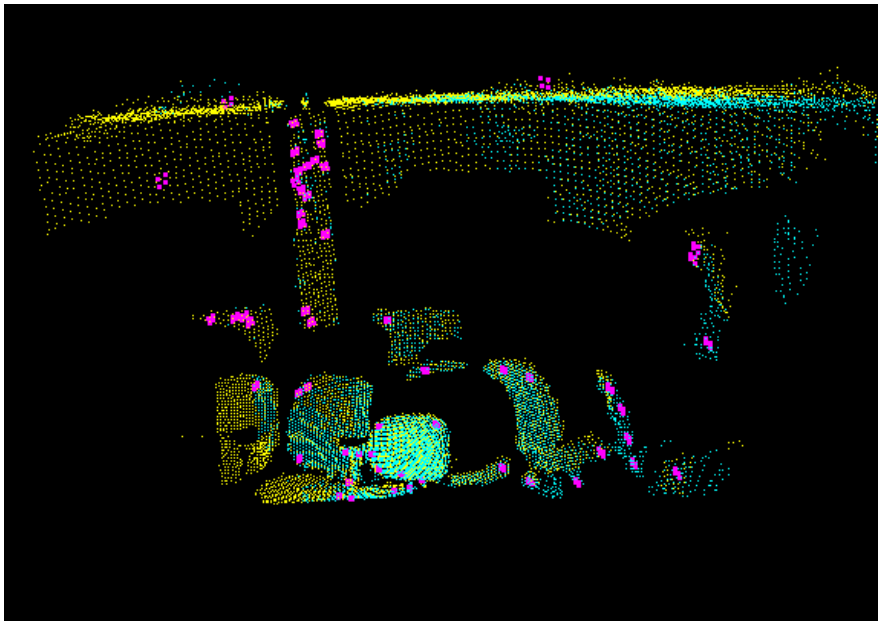


- Take two point clouds
- Find NARFs
- Match features and find transform
- Make transform and combine

3d SLAM

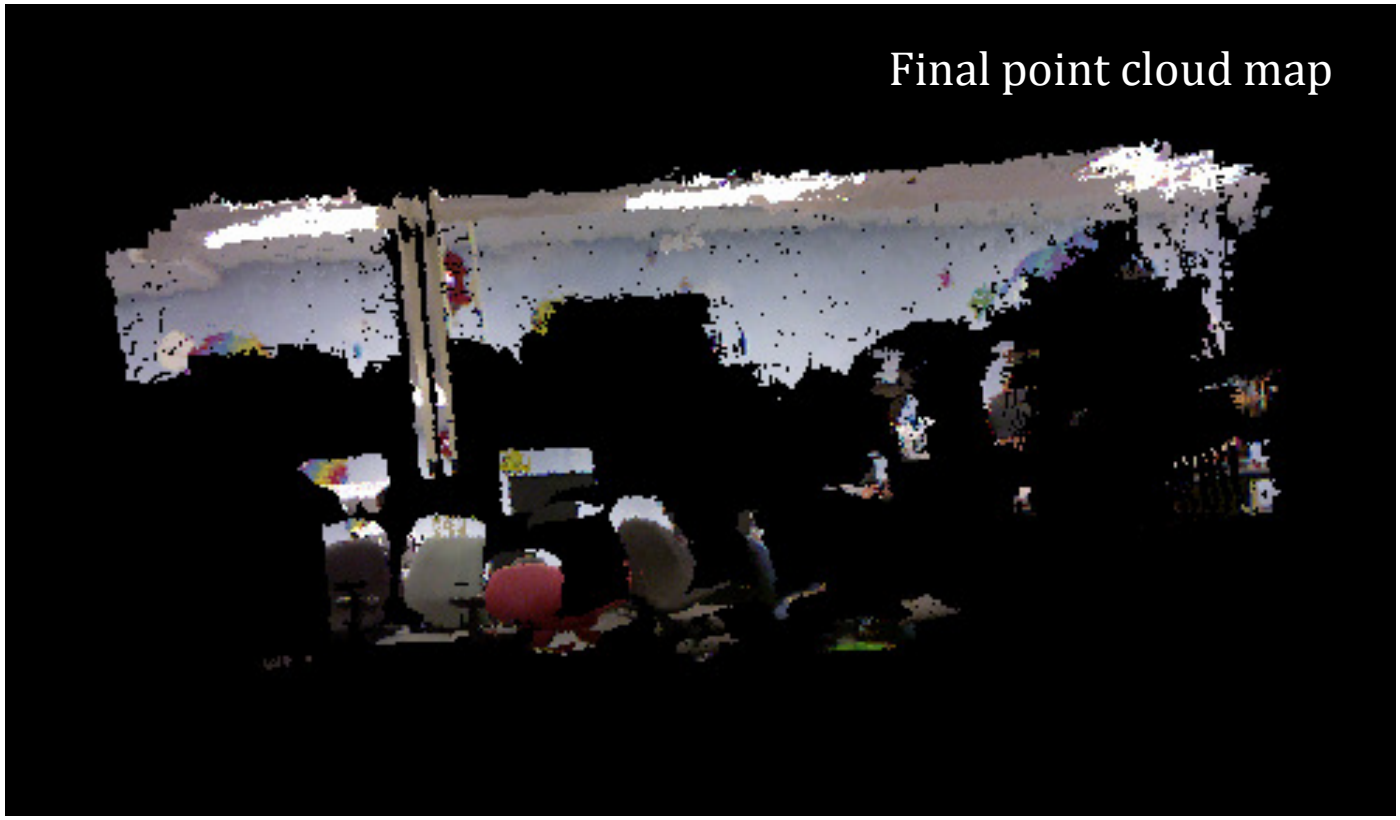
Simultaneous Localization And Mapping





- Take two point clouds
- Find NARFs
- Match features and find transform (ICP)
- Make transform and combine

3d SLAM



Questions?

Future: using Neato to create 2.5d maps

Kinect

Z.D. video

The Kinect estimates distance-to-camera by projecting a “star field” on the world.

Now vs. Then


DAD, HOW COME OLD PHOTOGRAPHS ARE ALWAYS BLACK AND WHITE? DIDN'T THEY HAVE COLOR FILM BACK THEN?
SURE THEY DID. IN FACT, THOSE OLD PHOTOGRAPHS ARE IN COLOR. IT'S JUST THE WORLD WAS BLACK AND WHITE THEN.
REALLY?
YEP. THE WORLD DIDN'T TURN COLOR UNTIL SOMETIME IN THE 1930s, AND IT WAS PRETTY GRAINY COLOR FOR A WHILE, TOO.
THAT'S REALLY WEIRD.
WELL, TRUTH IS STRANGER THAN FICTION.
BUT THEN WHY ARE OLD PAINTINGS IN COLOR?! IF THE WORLD WAS BLACK AND WHITE, WOULDN'T ARTISTS HAVE PAINTED IT THAT WAY?
NOT NECESSARILY. A LOT OF GREAT ARTISTS WERE INSANE.

Title


Calvin and Hobbes
by Watterson
WOW, HONEY, YOU'RE MISSING A BEAUTIFUL SUNSET OUT HERE!
I'LL COUNT TO 10, AND THEN... POW!
DAD, HOW COME OLD PHOTOGRAPHS ARE ALWAYS BLACK AND WHITE? DIDN'T THEY HAVE COLOR FILM BACK THEN?
SURE THEY DID. IN FACT, THOSE OLD PHOTOGRAPHS ARE IN COLOR. IT'S JUST THE WORLD WAS BLACK AND WHITE THEN.
REALLY?
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BUT THEN WHY ARE OLD PAINTINGS IN COLOR?! IF THE WORLD WAS BLACK AND WHITE, WOULDN'T ARTISTS HAVE PAINTED IT THAT WAY?
NOT NECESSARILY. A LOT OF GREAT ARTISTS WERE INSANE.
BUT...BUT HOW COULD THEY HAVE PAINTED IN COLOR ANYWAY? WOULDN'T THEIR PAINTS HAVE BEEN SHADES OF GRAY BACK THEN?
OF COURSE, BUT THEY TURNED COLORS LIKE EVERYTHING ELSE DID IN THE '30s.
SO WHY DIDN'T OLD BLACK AND WHITE PHOTOS TURN COLOR TOO?
BECAUSE THEY WERE COLOR PICTURES OF BLACK AND WHITE, REMEMBER?
THE WORLD IS A COMPLICATED PLACE, HOBBES.
WHENEVER IT SEEMS THAT WAY, I TAKE A NAP IN A TREE AND WAIT FOR DINNER.

Accessing these models

plane

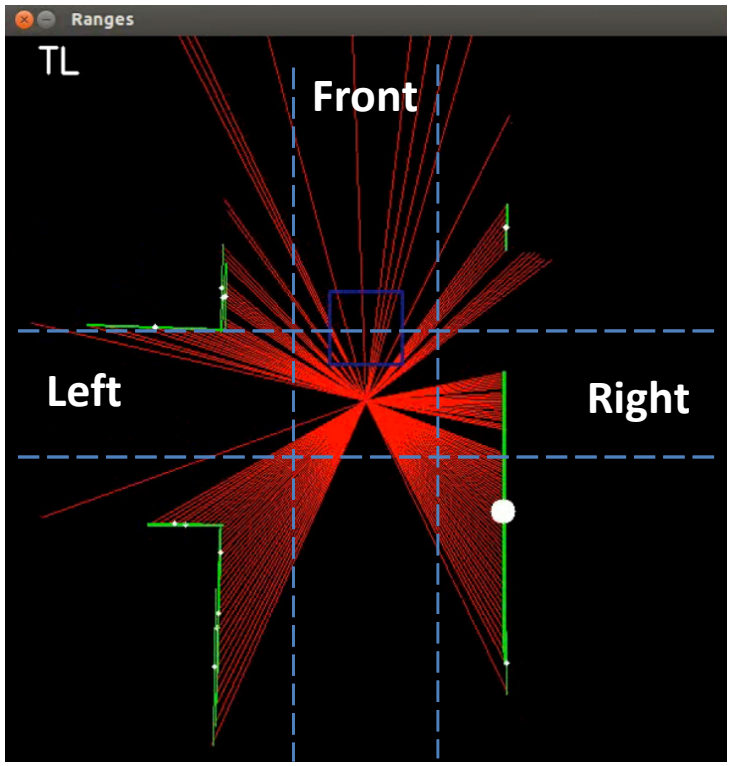
other (sphere, cylinder, wavy,…)
K.M.

allows us to define the depth at each pixel

Ideally, a camera-only system could localize – *and reason* – within the 3d model

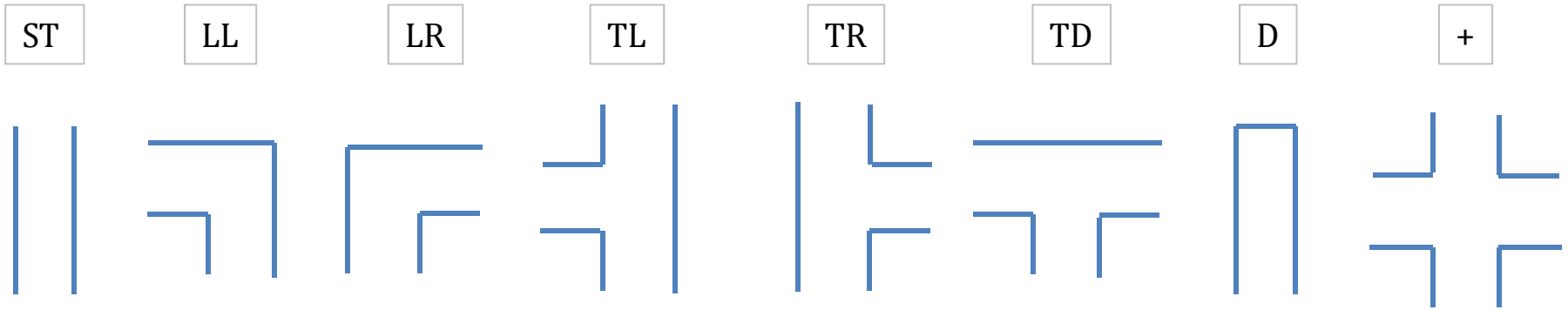
Ideally, a camera-only system could localize – *and reason* – within the 3d model

Intersection recognition

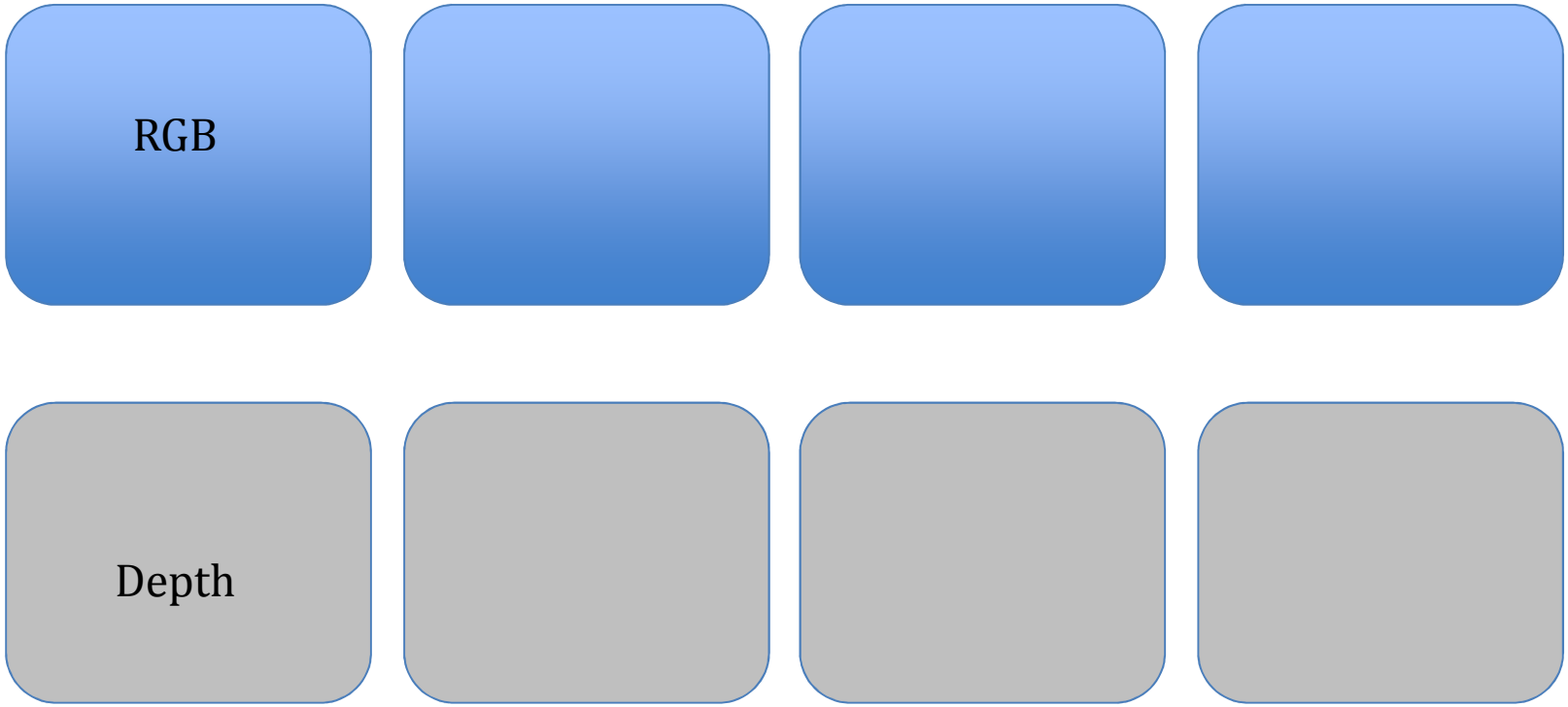


For each scan:

- Check for **Front**, **Left**, and **Right** obstacles
- The number of obstacles determines the intersection type 3:**D** 2:**L** 1:**T** 0:**+**
- Open space determines final label, e.g., **TL**
- After 15 recognitions in a row, the robot checks the map (by broadcasting a message)
- The robot does not broadcast again until it resets in a hallway: **ST**.

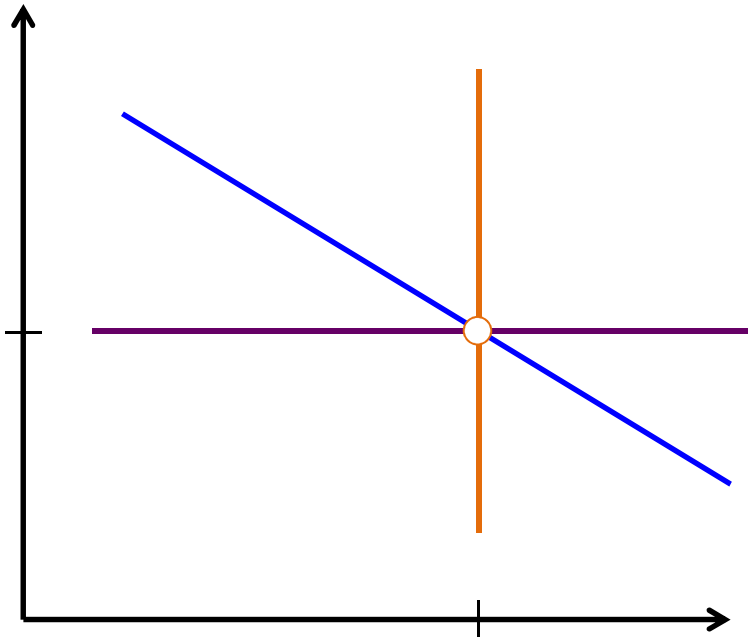


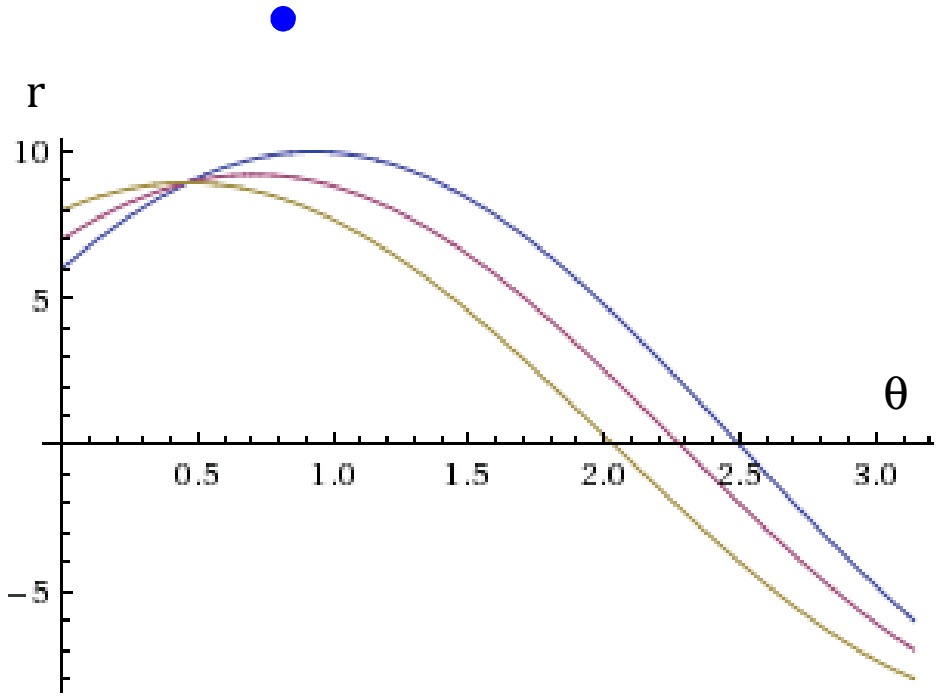
Accessing 3d models



splicing into the code…

Hough transform





Consider ***one point*** of a laser scan

These are ***all*** of the lines through it

http://gmarty.github.io/hough-transform-js/

http://liquify.eu/flash/HoughTransform