January 15th, 2009

Matt Walter, mwalter@mit.edu

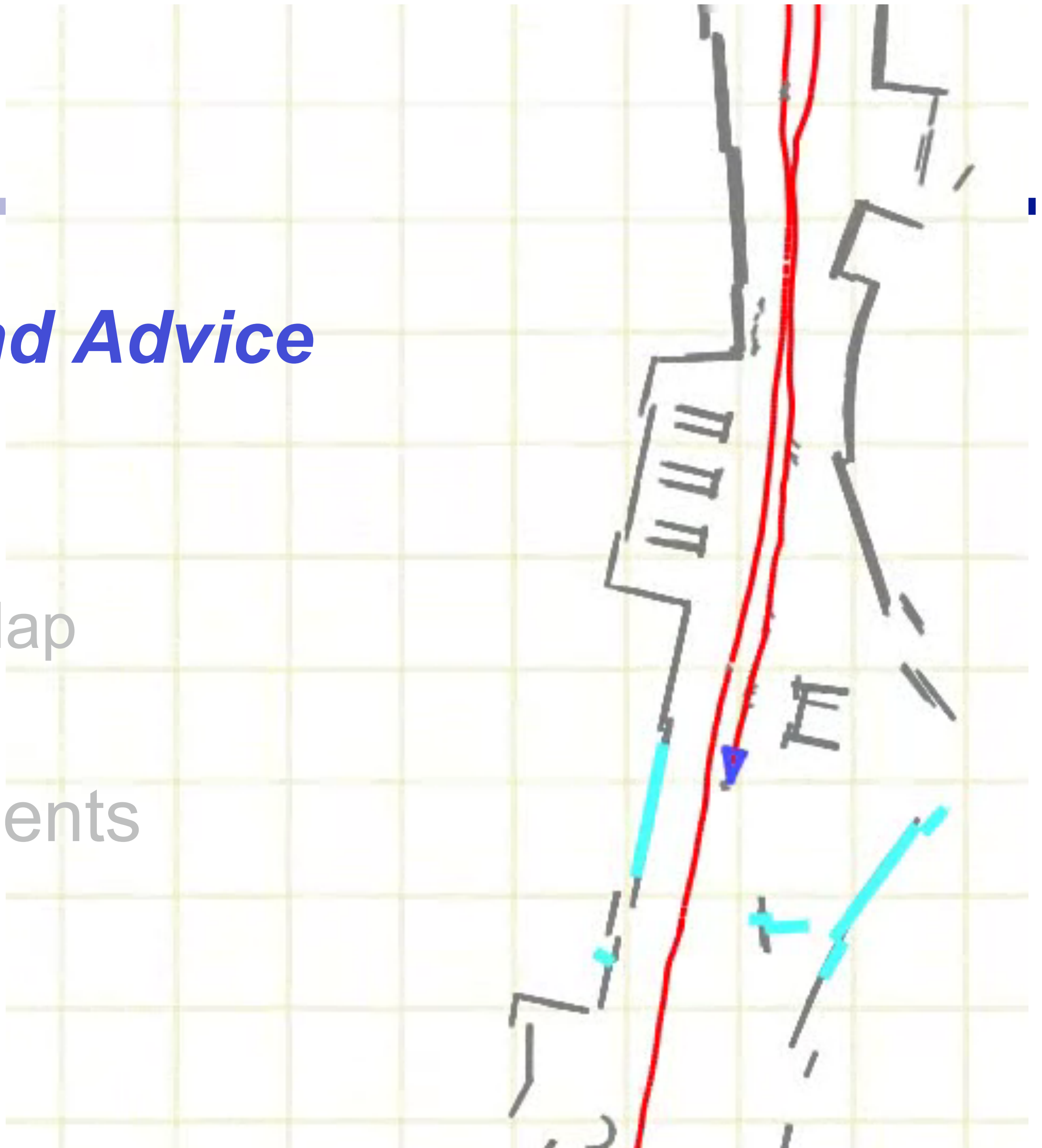
- Slides courtesy of Edwin Olson

Goals for this talk

- Why should I build a map?
- Three mapping algorithms
  - Forgetful local map
    - Really easy, very useful over short time scales (a minute?)
  - Topological roadmap
    - Also really easy, moderately useful over arbitrary time scales
  - World’s simplest—but powerful—SLAM algorithm
    - A taste of the “real thing”.

Attack Plan

- ***Motivation and Advice***
- Algorithms:
  - Forgetful Map
  - Topological Map
  - SLAM
- Sensor Comments



Why build a map?

- Playing field is big, robot is slow
- Driving around perimeter takes a minute!

- Scoring takes time… often ~20 seconds to “line up” to a mouse hole.

- Be able to efficiently move to specific locations that we have previously seen
  - I’ve got a bunch of balls, where’s the nearest goal?
- Be able to efficiently explore unseen areas
  - Don’t re-explore the same areas over and over
- Build a map for its own sake
  - No better way to *wow* your competition/friends.

A little advice

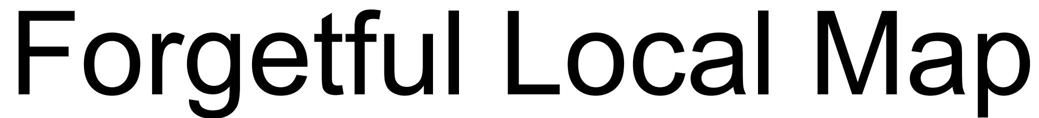
- Mapping is hard! And it’s not *required* to do okay.
  - Concentrate on basic robot competencies *first*
  - Design your algorithms so that map information *is helpful*, but *not required*
  - Pick your mapping algorithm judiciously
    - Pick something you’ll have time to implement *and* test
    - Lots of newbie gotchas, like 2pi wrap-around

Visualization

- Visualization is critical
  - *Impossible* to debug your code unless you can see what’s happening
  - Write code to view your maps and publish them!
  - Nobody will appreciate your map if they can’t see it.

Attack Plan

- Motivation and Advice
- Algorithms:
  - ***Forgetful Map***
  - Topological Map
  - SLAM
- Sensor Comments



Forgetful Local Map

- It’s as good as your dead-reckoning
- Estimate your dead-reckoning error, don’t use data that’s useless.
  - Don’t throw it away though– *log* it.
- Easy to implement

Dead-Reckoning

- Compute robot’s position in an arbitrary coordinate system

$$x = \sum d_i * \cos(\theta_i)$$

$$y = \sum d_i * \sin(\theta_i)$$

$$\theta_i = \sum \Delta\theta_i$$

- Easy to compute:
  - Get d_i from wheel encoders (or back EMF-derived velocity?)
  - Get $\Delta\theta_i$ from gyro
    - Actually, integration done for you

The problem with dead-reckoning

- Error accumulates over time
  - Really fast– errors in θ_i cause *super-linear* increases in error
  - Use zero-velocity update
- Distance error proportional to measured distance
  - Anywhere from 10-50% depending on sensors, terrain
- Gyro error grows over function of *time*.
  - About 1-5 degrees per minute.

World's simplest (metrical) map

- Every time you see something, record it in a list
- Looking for something?
  - Search *backwards* in the list
- Don't use old data
  - Estimate distance/theta error by subtracting cumulative error estimates
  - If theta error > 30 degrees or so → bearing is bad
  - If distance error > 30% of distance to object → distance is bad
  - (These constants made up– you'll need to experiment!)

Older data ↑

Cumulative Distance/ Orientation error	What	Location (x,y)
(0.2, 0.1)	Goal	(2.3, 1.1)
(0.4, 0.15)	Robot Pose	(2.0, 1.0)
(1.0, 0.2)	Barcode	2.4, 1.2)
(2.0, 0.22)	Barcode	(3.5, .3)
(2.5, 0.3)	Robot Pose	(3.0, 1.0)
…	…	…

Zero-velocity updates

- Gyros accumulate error as a function of *integration time*
  - Even if you're not moving
- Idea: if robot is stationary, *stop* gyro integration → stop error accumulation

Attack Plan

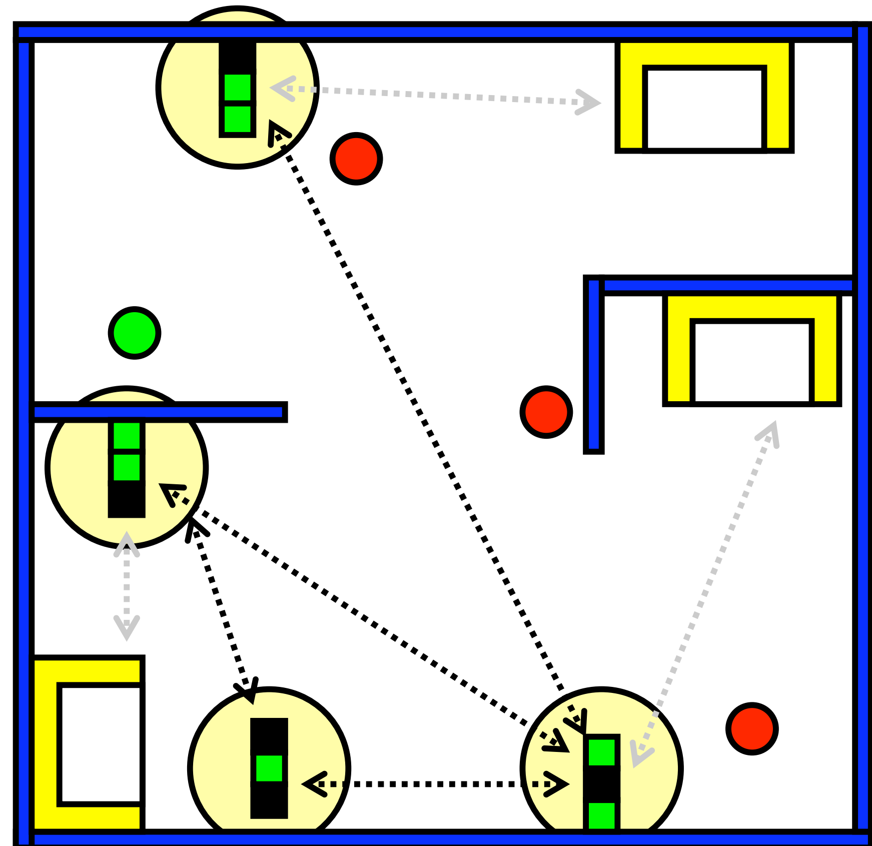
- Motivation and Advice
- Algorithms:
  - Forgetful Map
  - ***Topological Map***
  - SLAM
- Sensor Comments

Topological Maps

- Learn and remember invariant properties in the world:
  - “I can see barcodes 3 and 7 when I’m sitting next to barcode 12”
- De-emphasize *metrical* data
  - Maybe remember “when I drove directly from barcode 2 to barcode 7, it was about 3.5 meters”
- Very easy!
  - But you can probably only put barcodes (maybe goals) into the map

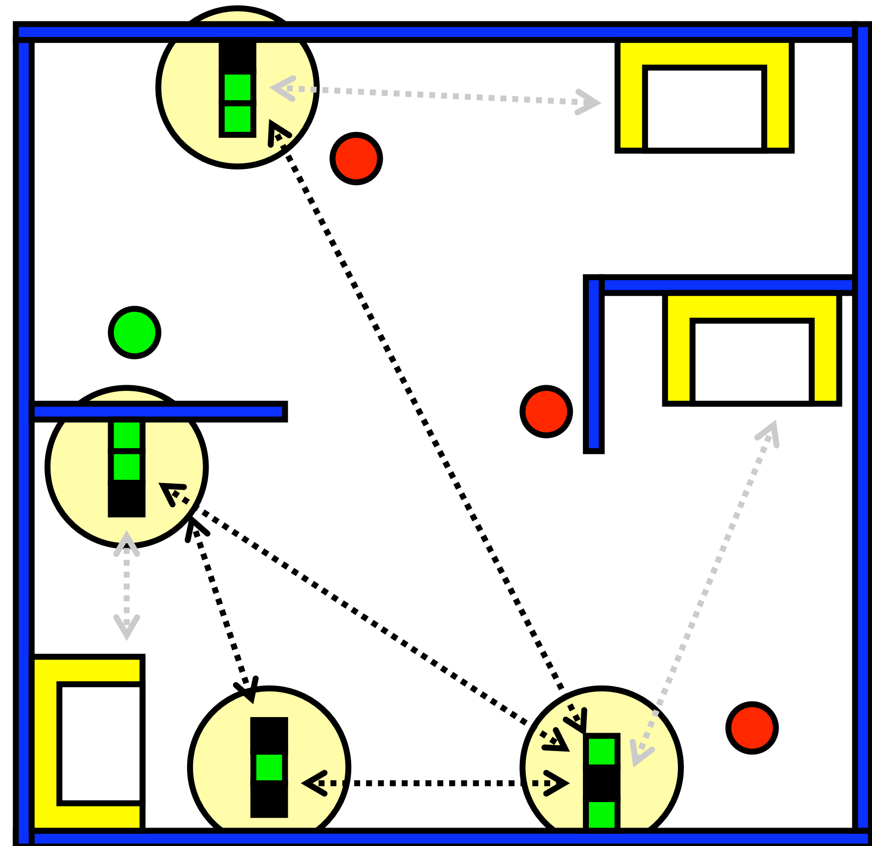
Topological Maps

- Nodes in graph are easily identifiable features
  - e.g. barcodes, goals
- Each node lists things “near” or visible to it
  - Other bar codes
  - Goals, maybe balls
- Implicitly encode obstacles
  - Walls obstruct visibility!
- Want to get somewhere?
  - Drive to the nearest barcode, then follow the graph.



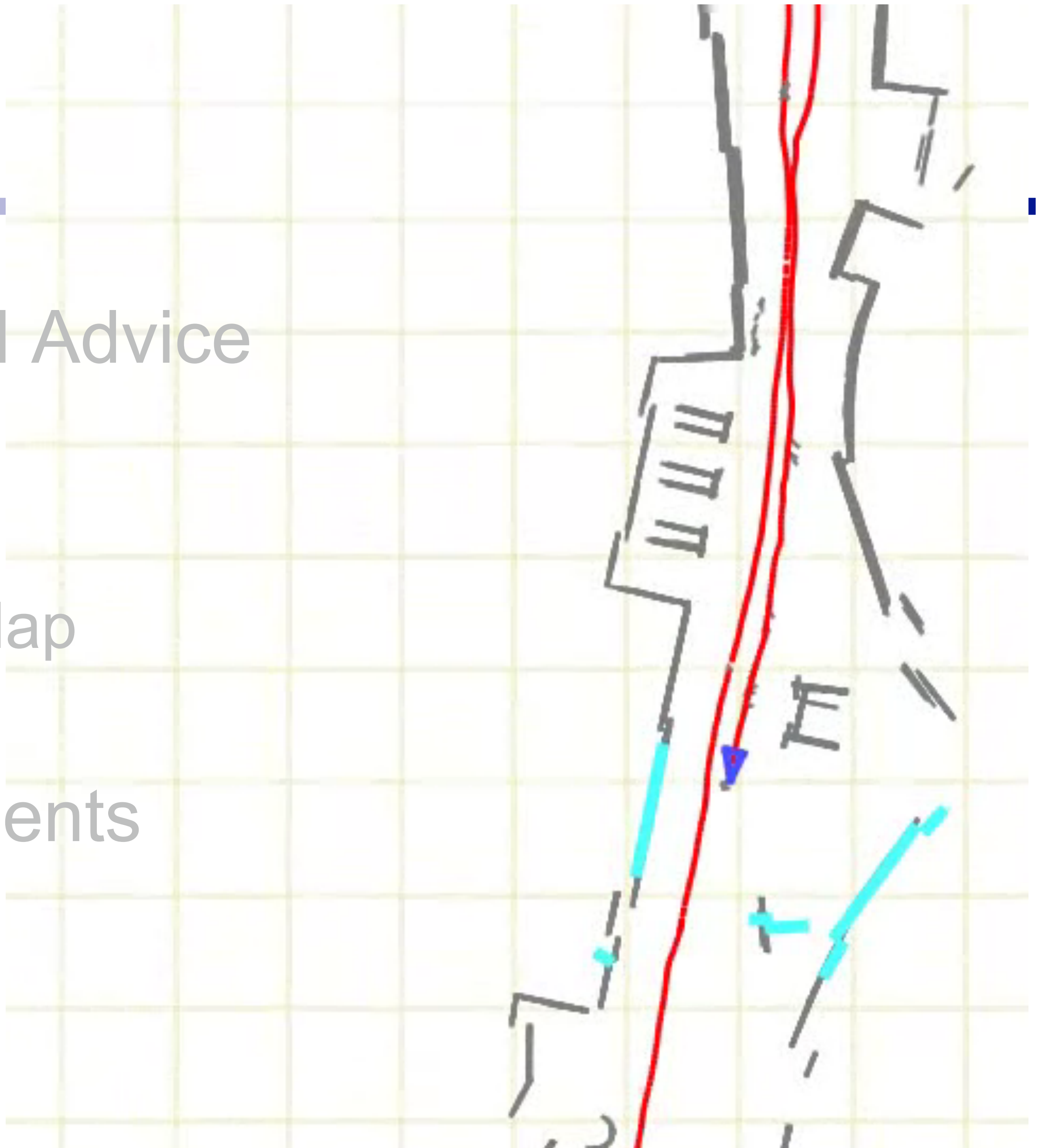
Topological Maps - Challenges

- Building map takes time
  - Repeated 360 degree sensor sweeps
- Solutions sub-optimal
  - (But better than random walk!)
- You may have to resort to random walking when your graph is incomplete
- Hard to visualize since you can't recover the actual positions of nodes



Attack Plan

- Motivation and Advice
- Algorithms:
  - Forgetful Map
  - Topological Map
  - ***SLAM***
- Sensor Comments



Brute-Force SLAM

- Simultaneous Localization and Mapping (SLAM)

- The following approach is exact, complete
  - (Is used in the “real world”)
  - I’ll show a version that works, but isn’t particularly scalable.

- Break out the 18.06!
  - Weren’t paying attention? Quick refresher coming…

Quick math review

- *Linear* approximation to arbitrary functions
- $f(x) = x^2$
  - *near x = 3,* $f(x) \approx 9 + 6\,(x\text{-}3)$

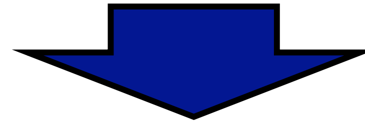
$$f(3) + \frac{df}{dx} * (x-3)$$

- *f(x,y,z) = (some mess)*
  - *near* (x_0, y_0, z_0)*:* $f(x) \approx F_0 + \left[\frac{df}{dx} \quad \frac{df}{dy} \quad \frac{df}{dz}\right] \begin{vmatrix} \Delta x \\ \Delta y \\ \Delta z \end{vmatrix}$

Quick math review

From previous slide:

$$f(x) = f_0 + \left[\frac{df}{dx} \quad \frac{df}{dy} \quad \frac{df}{dz} \right] \begin{vmatrix} \Delta x \\ \Delta y \\ \Delta z \end{vmatrix}$$



Re-arrange:

$$\left[\frac{df}{dx} \quad \frac{df}{dy} \quad \frac{df}{dz} \right] \begin{vmatrix} \Delta x \\ \Delta y \\ \Delta z \end{vmatrix} = f(x) - f_0$$

Linear Algebra notation:

$$J \quad d = r$$

Example

- We observe range z_d and heading z_θ to a feature.
  - We express our observables in terms of the state variables (x_* y_* $theta_*$) and noise variables (v_*)

$$h = \begin{pmatrix} z_d = [(x_f - x_r)^2 + (y_f - y_r)^2]^{1/2} + v_d \\ z_\theta = \arctan 2(y_f - y_r, x_f - x_r) - x_\theta + v_\theta \end{pmatrix}$$

Example

$$h = \begin{pmatrix} z_d = [(x_f - x_r)^2 + (y_f - y_r)^2]^{1/2} + v_d \\ z_\theta = \arctan 2(y_f - y_r, x_f - x_r) - x_\theta + v_\theta \end{pmatrix}$$

- Compute a *linear* approximation of these constraints:
  - Differentiate these constraints with respect to the state variables
  - End up with something of the form Jd = r

Example

$$h = \begin{pmatrix} z_d = [(x_f - x_r)^2 + (y_f - y_r)^2]^{1/2} + v_d \\ z_\theta = \arctan 2(y_f - y_r, x_f - x_r) - \theta_r + v_\theta \end{pmatrix}$$

A convenient substitution: $\lambda = 1/(1+(d_y/d_x))^2$

$$d_x = x_f - x_r$$

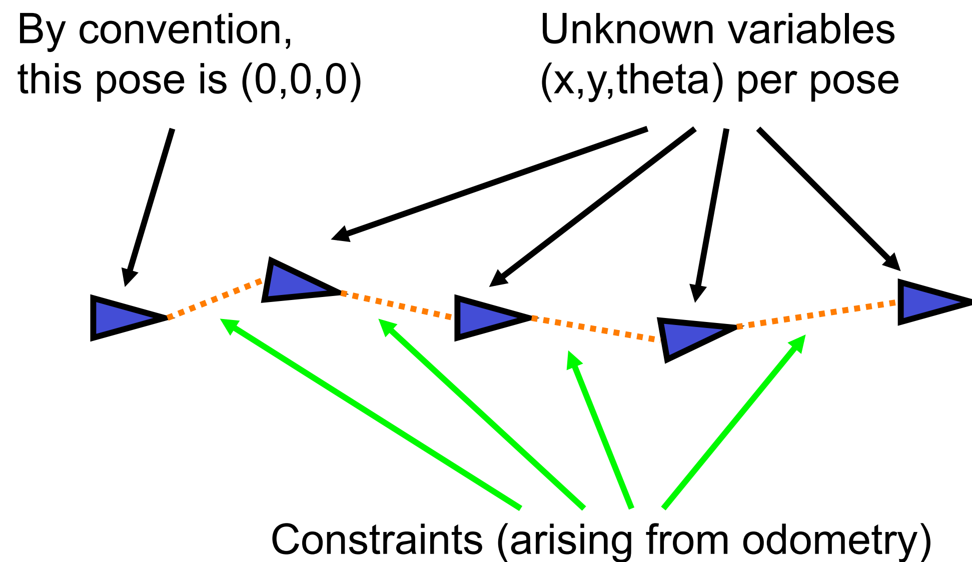
$$d_y = y_f - y_r$$

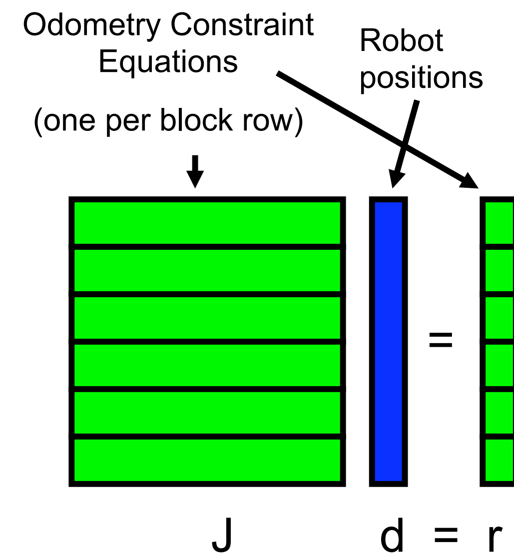
	x_r	y_r	$theta_r$	x_f	y_f
z_d	$-d_x/d$	$-d_y/d$	0	d_x/d	d_y/d
z_{theta}	$\lambda d_y/d_x^2$	$-\lambda/d_x$	-1	$-\lambda d_y/d_x^2$	λ/d_x

$$J = \begin{vmatrix} -d_x/d & -d_y/d & 0 & d_x/d & d_y/d \\ \lambda d_y/d_x^2 & -\lambda/d_x & -1 & -\lambda d_y/d_x^2 & \lambda/d_x \end{vmatrix}$$

H = Jacobian of **h** with respect to **x**

Metrical Map example

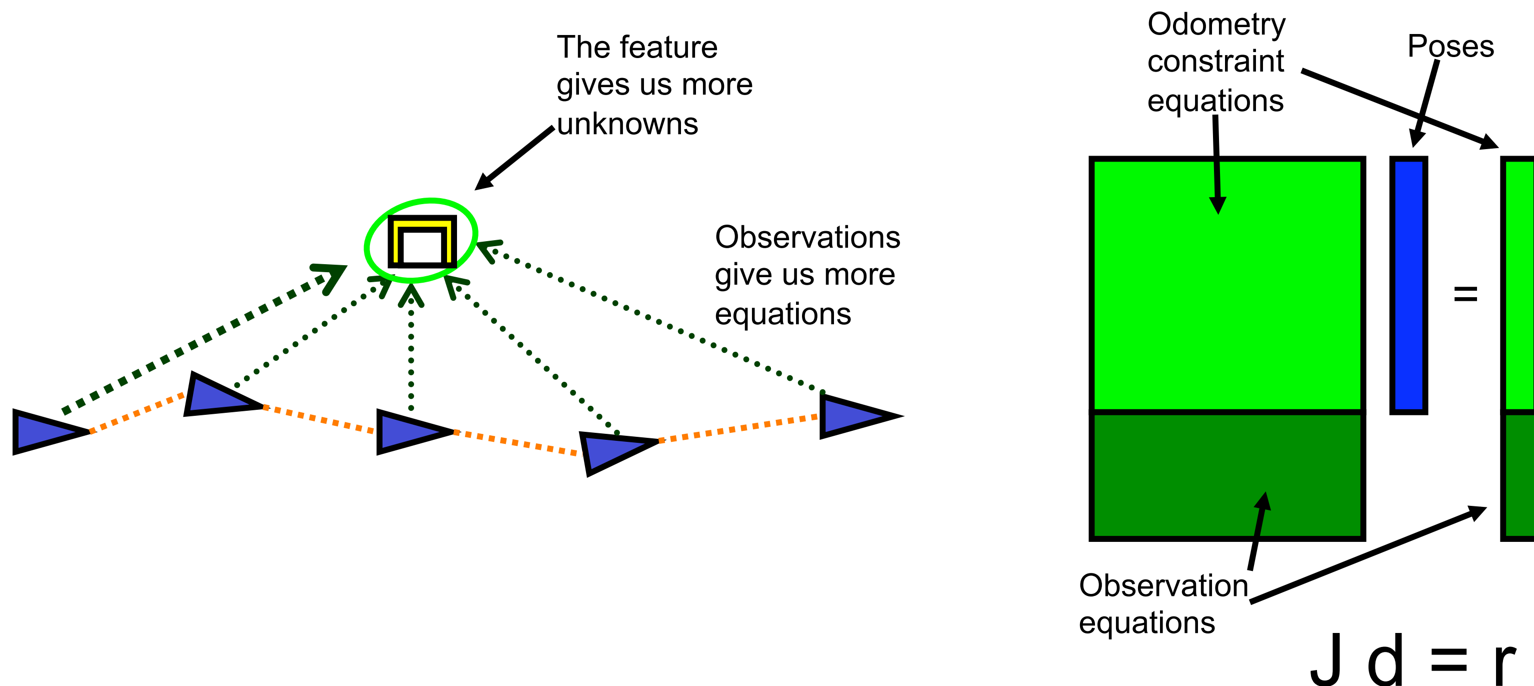




number unknowns==number of equations, solution is critically determined.

$$d = J^{-1}r$$

Metrical Map example



number unknowns < number of equations, solution is *over determined.*
Least-squares solution is:

$$d = (J^T J)^{-1} J^T r$$

More equations = better pose estimate

Computational Cost

- The least-squares solution to the mapping problem:

$$d = (J^T W J)^{-1} J^T W b$$

(W=weight matrix)

$$x_{i+1} = x_i + d$$

- Must invert* a matrix of size 3Nx3N (N = number of poses.) Inverting this matrix costs $O(N^3)$!
  - N is pretty small for Maslab
  - How big can N get before this is a problem?

- JAMA, Java Matrix library

* We'd never actually invert it; it's better to use a Cholesky Decomposition or something similar (A\b in Matlab). But it has the same computational complexity. JAMA will do the right thing.

State of the Art

- Simple! Just solve

$$d = \left(J^T W J\right)^{-1} J^T W b$$

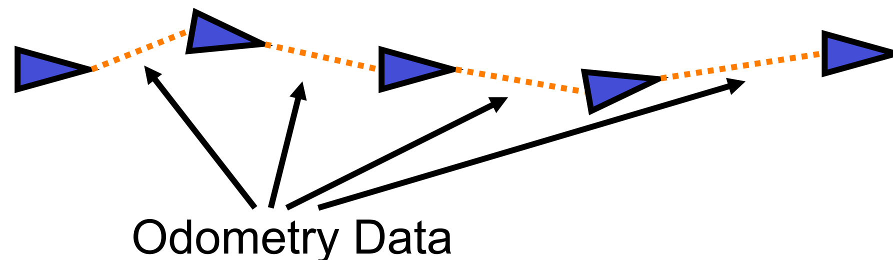
faster, using less memory.

What does all this math get us?

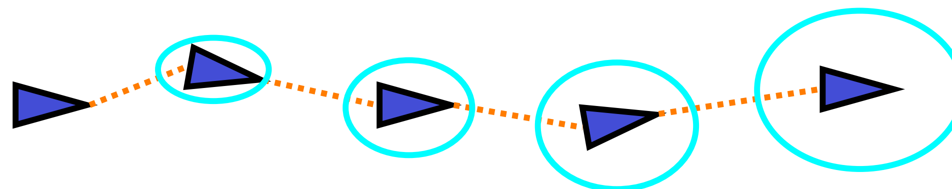
- Okay, so why bother?

Odometry Trajectory

- Integrating odometry data yields a trajectory

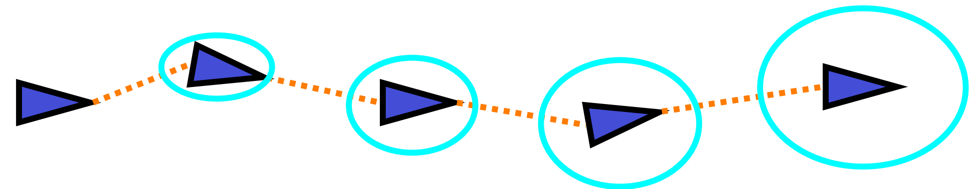


- Uncertainty of pose increases at every step



Metrical Map example

1. Original Trajectory with odometry constraints

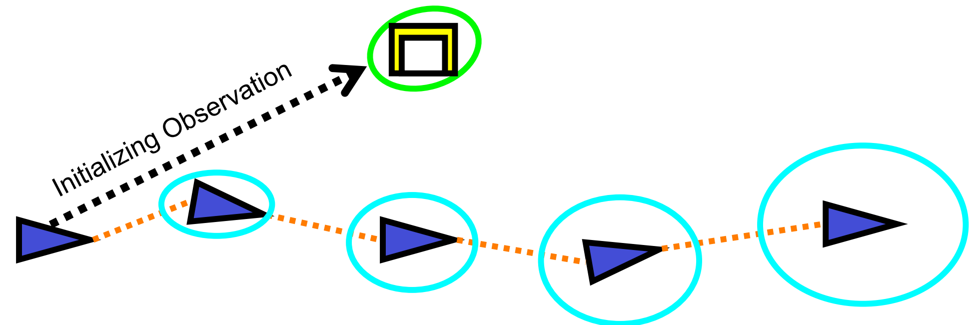


2. Observe external feature

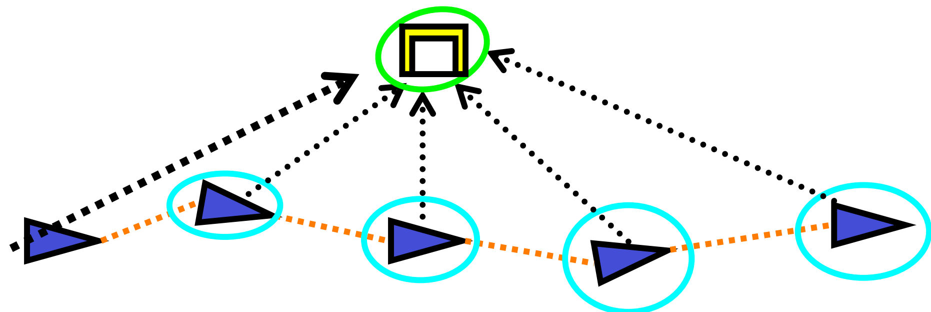
   Initial feature uncertainty =

   pose uncertainty +

   observation uncertainty

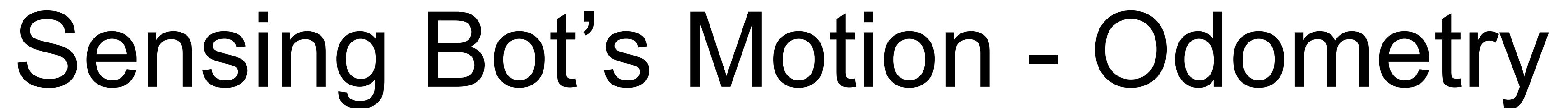


3. Reobserving feature helps subsequent pose estimates



Attack Plan

- Motivation and Advice
- Algorithms:
  - Forgetful Map
  - Topological Map
  - SLAM
- ***Sensor Comments***



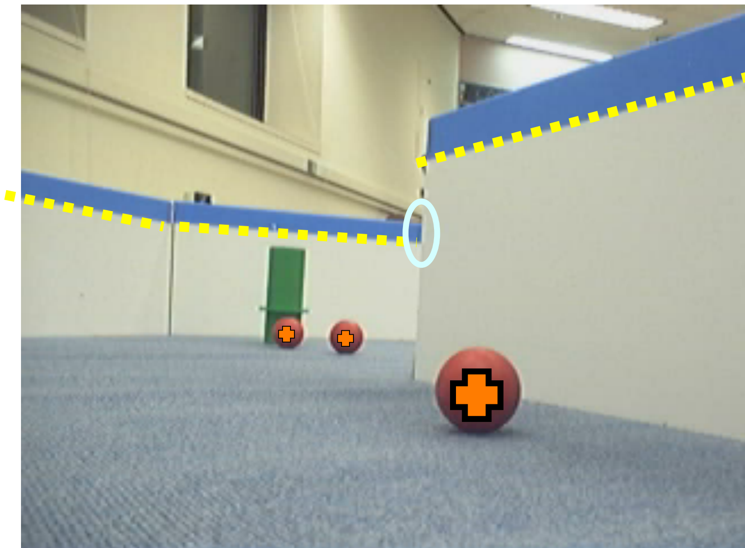
Sensing Bot’s Motion - Odometry

- Roboticists bread-and-butter
  - You should use odometry in some form, if only to detect if your robot is moving as intended
- “Dead-reckoning” : estimate motion by counting wheel rotations
  - Encoders (binary or quadrature phase)
  - Maslab-style encoders are very poor
- Motor modeling
  - Model the motors, measure voltage and current across them to infer the motor angular velocity
  - Angular velocity can be used for dead-reckoning
  - Pretty lousy method, but possibly better than low-resolution flaky encoders

http://orcboard.org/documentation/odomtutorial.pdf

Observing the World - Camera

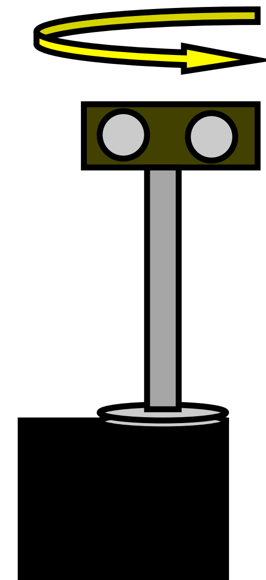
- Useful features can be extracted!
  - Lines from white/blue boundaries
  - Balls (great point features! Just delete them after you've moved them.)
  - "Accidental features"
- You can estimate bearing *and* distance.
  - Camera mounting angle has effect on distance precision
- Triangulation
  - Make bearing measurement
  - Move robot a bit (keeping odometry error small)
  - Make another bearing measurement

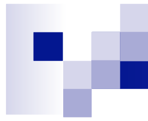


More features = better navigation performance

Range finders

- Range finders are most direct way of locating walls/obstacles.
- Build a "LADAR" by putting a range finder on a servo
  - High quality data! Great for mapping!
  - Terribly slow.
    - At least a second per scan.
      - With range of > 1 meter, you don't have to scan very often.
    - Two range-finders = twice as fast
      - Or alternatively, 360° coverage
    - Hack servo to read analog pot directly
      - Then slew the servo in one command at maximum speed instead of stepping.
    - Add gearbox to get 360° coverage with only one range finder.





Questions?

Extended Kalman Filter

- x : vector of all the state you care about (same as before)
- P : covariance matrix (same as $(J^TWJ)^{-1}$ before)

- Time update:
  - $x' = f(x,u,0)$ ← integrate odometry
  - $P = APA^T + BQB^T$ ← adding noise to covariance

A = Jacobian of ***f*** wrt ***x***

B = Jacobian of noise wrt **x**

Q = covariance of odometry

Metrical Map - Weighting

- Some sensors (and constraints) better than others
- Put *weights* in block-diagonal matrix W

weight of eqn 1
weight of eqn 2

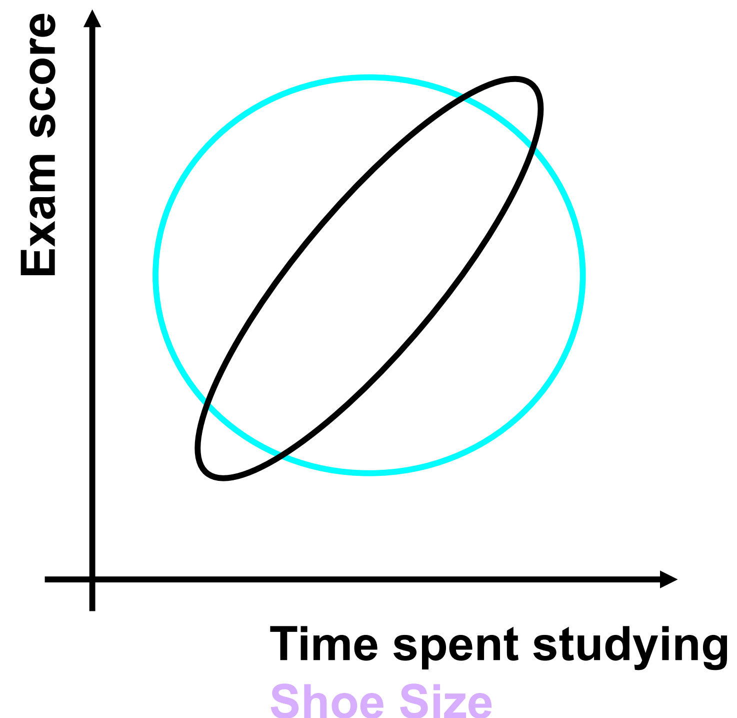
W =

$$d = (J^T W J)^{-1} J^T W r$$

- What is the interpretation of $J^T W J$?

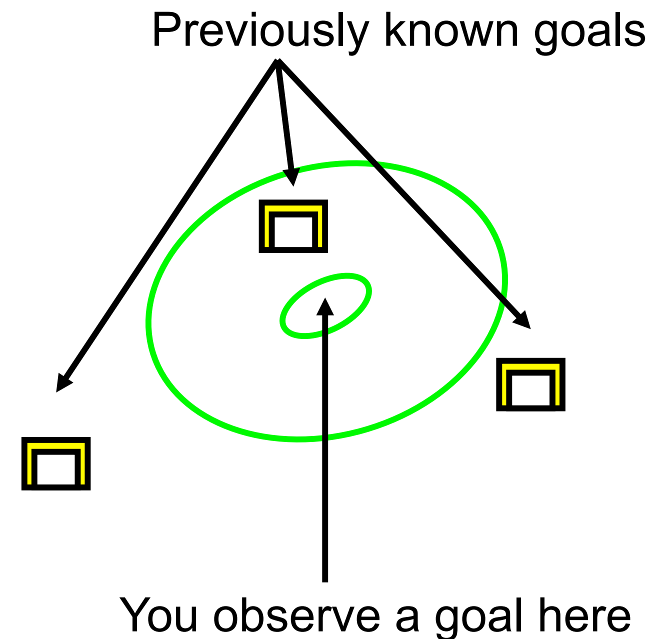
Correlation/Covariance

- In multidimensional Gaussian problems, equal-probability contours are ellipsoids.
- Shoe size doesn't affect grades:
  P(grade,shoesize)=P(grade)P(shoesize)
- Studying helps grades:
  P(grade,studytime)!=P(grade)P(studytime)
  - We must consider P(x,y) jointly, respecting the correlation!
  - If I tell you the grade, you learn something about study time.



Why is covariance useful?

- Loop Closing (and Data Association)
- Suppose you observe a goal (with some uncertainty)
  - Which previously-known goal is it?
  - Or is it a new one?
- Covariance information helps you decide
  - If you can tell the difference between goals, you can use them as navigational land marks!



Extended Kalman Filter

- Observation
  - $K = PH^T(HPH^T + VRV^T)^{-1}$ ← Kalman "gain"
  - $x' = x + K(z - h(x,0))$
  - $P = (I - KH)P$

H = Jacobian of *constraint* wrt ***x***

B = Jacobian of noise wrt **x**

R = covariance of *constraint*

- P is your covariance matrix
  - Just like $(J^TWJ)^{-1}$

Kalman Filter: Properties

- You incorporate sensor observations one at a time.
- Each successive observation is the same amount of work (in terms of CPU).
- *Yet, the final estimate is the* ***global*** *optimal solution.*
  - The same solution we would have gotten using least-squares. Almost.

The Kalman Filter is an *optimal,*

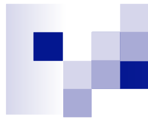
recursive estimator.

Kalman Filter: Properties

- In the limit, features become highly correlated
  - Because observing one feature gives information about other features
- Kalman filter computes the *posterior pose*, but **not** the posterior *trajectory*.
  - If you want to know the path that the robot traveled, you have to make an extra “backwards” pass.

Kalman Filter: Shortcomings

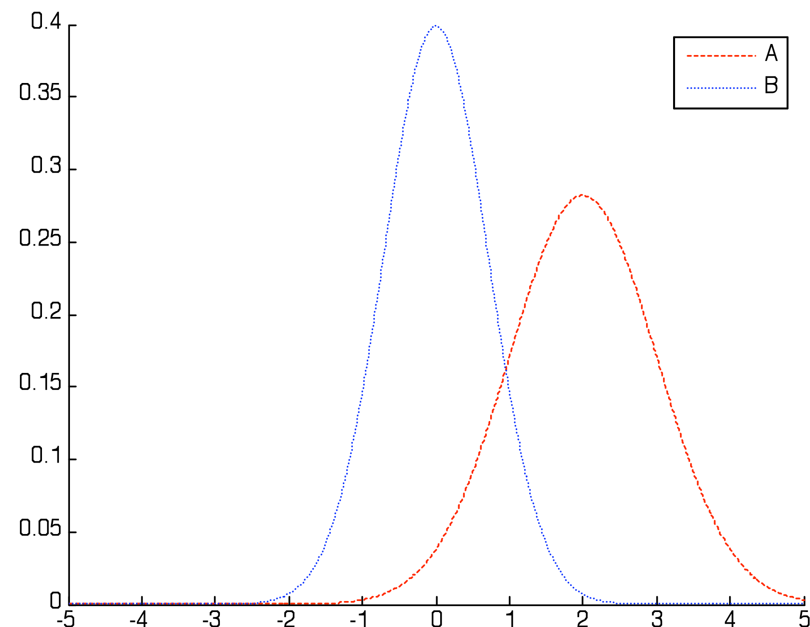
- With N features, update time is still large: $O(N^2)$!
- For Maslab, N is small. Who cares?
- In the "real world", N can be $>>10^6$.
- Linearization Error
- Current research: lower-cost mapping methods



Old Slides

Kalman Filter

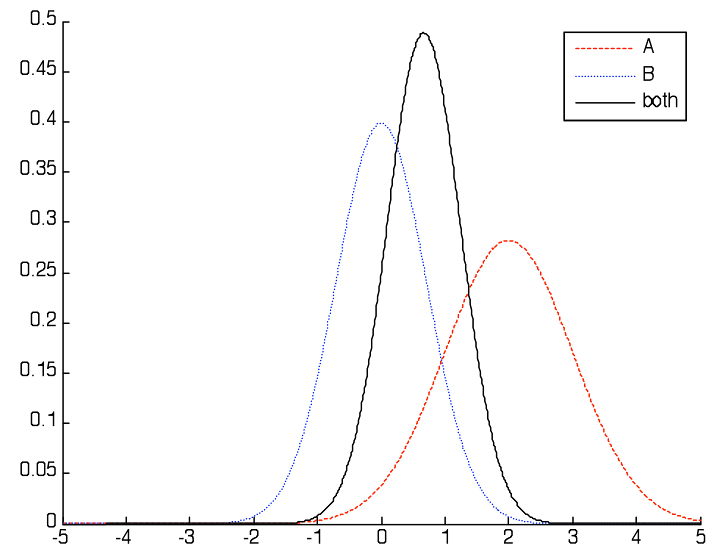
- Example: Estimating where Jill is standing:
  - Alice says: x=2
    - We think **σ²** =2; she wears thick glasses
  - Bob says: x=0
    - We think **σ²** =1; he's pretty reliable



- How do we combine these measurements?

Simple Kalman Filter

- Answer: algebra (and a little calculus)!
  - Compute mean by finding maxima of the log probability of the product $P_A P_B$.
  - Variance is messy; consider case when $P_A=P_B=N(0,1)$
- *Try deriving these equations at home!*



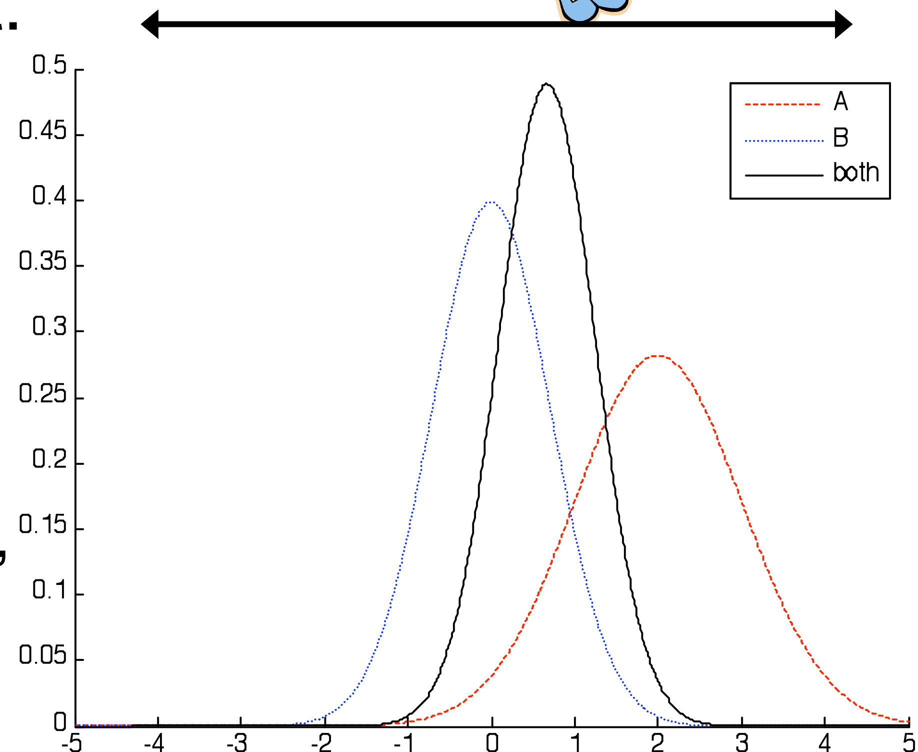
$$\frac{1}{\sigma^2} = \frac{1}{\sigma_A^{\ 2}} + \frac{1}{\sigma_B^{\ 2}}$$

$$\mu = \frac{\mu_A \sigma_B^{\ 2} + \mu_B \sigma_A^{\ 2}}{\sigma_A^{\ 2} + \sigma_B^{\ 2}}$$

Kalman Filter Example

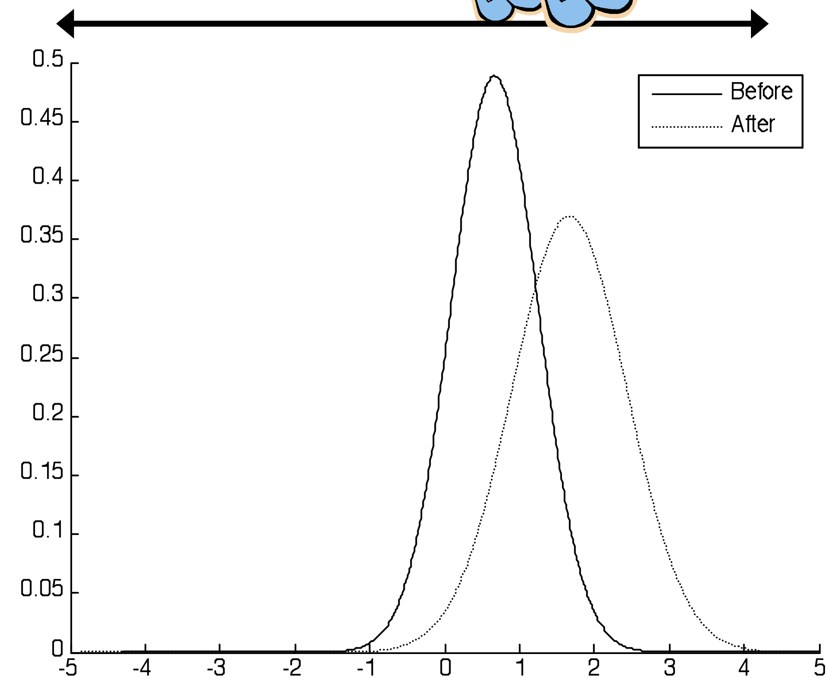
- We now think Jill is at:
  - $x = 0.66$
  - $\sigma^2 = 0.66$

- Note: Observations *always* reduce uncertainty
  - Even in the face of conflicting information, EKF never becomes less certain.



Kalman Filter

- Now Jill steps forward one step
- We think one of Jill's steps is about 1 meter, $\sigma^2 = 0.5$
- We estimate her position:
  - $x = x_{before} + x_{change}$
  - $\sigma^2 = \sigma_{before}^2 + \sigma_{change}^2$
- Uncertainty *increases*



Data Association

- Data association: The problem of recognizing that an object you see now is the same one you saw before
  - Hard for simple features (points, lines)
  - Easy for “high-fidelity” features (barcodes, bunker hill monuments)
- With perfect data association, most mapping problems become “easy”

Data Association

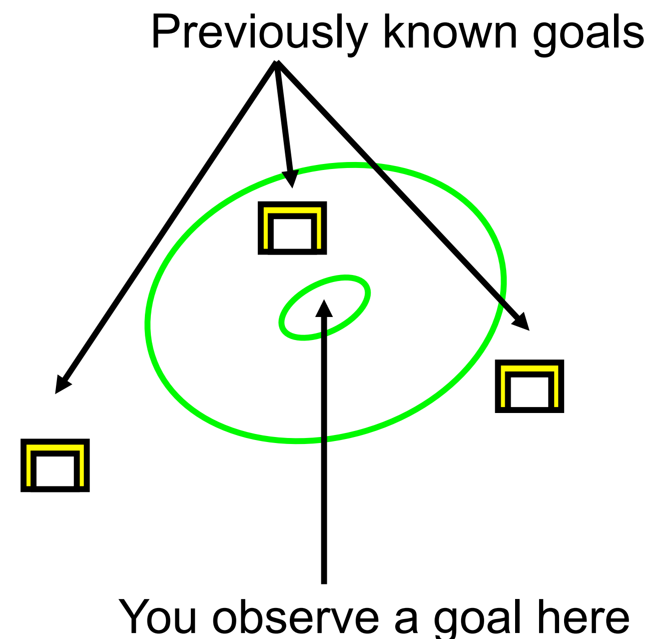
- If we can’t tell when we’re reobserving a feature, we don’t learn anything!
  - We need to observe the same feature *twice* to generate a constraint.

Data Association: Bar Codes

- Trivial!
- The Bar Codes have unique IDs; read the ID.

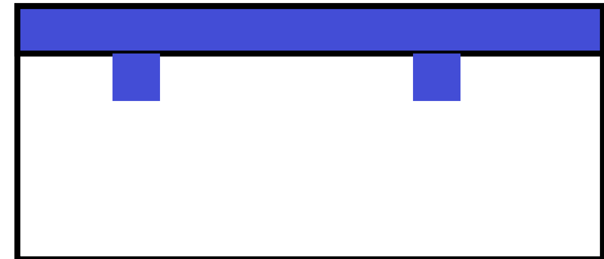
Data Association: Nearest Neighbor

- Nearest Neighbor
  - Simplest data association "algorithm"
  - Only tricky part is determining when you're seeing a brand-new feature.



Data Association: Tick Marks

- The blue tick marks can be used as features too.
  - Probably hard to tell that a particular tick mark is the one you saw 4 minutes ago…
  - You only need to reobserve the same feature *twice* to benefit!
  - If you can track them over short intervals, you can use them to improve your dead-reckoning.
    - Use nearest-neighbor. Your frame-to-frame uncertainty should only be a few pixels.

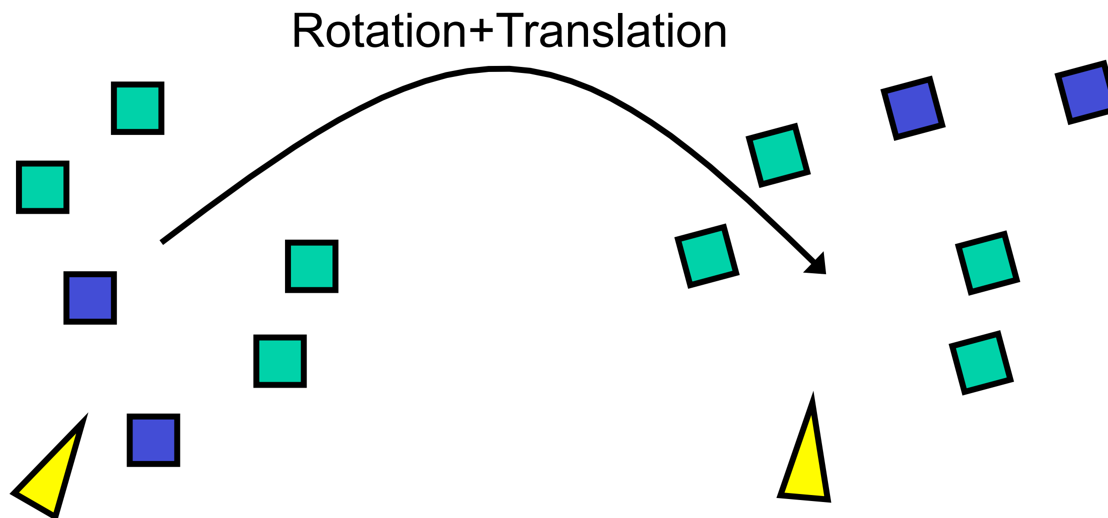


Data Association: Tick Marks

- Ideal situation:
  - Lots of tick marks, randomly arranged
  - Good position estimates on all tick marks
- Then we search for a *rigid-body-transformation* that best aligns the points.

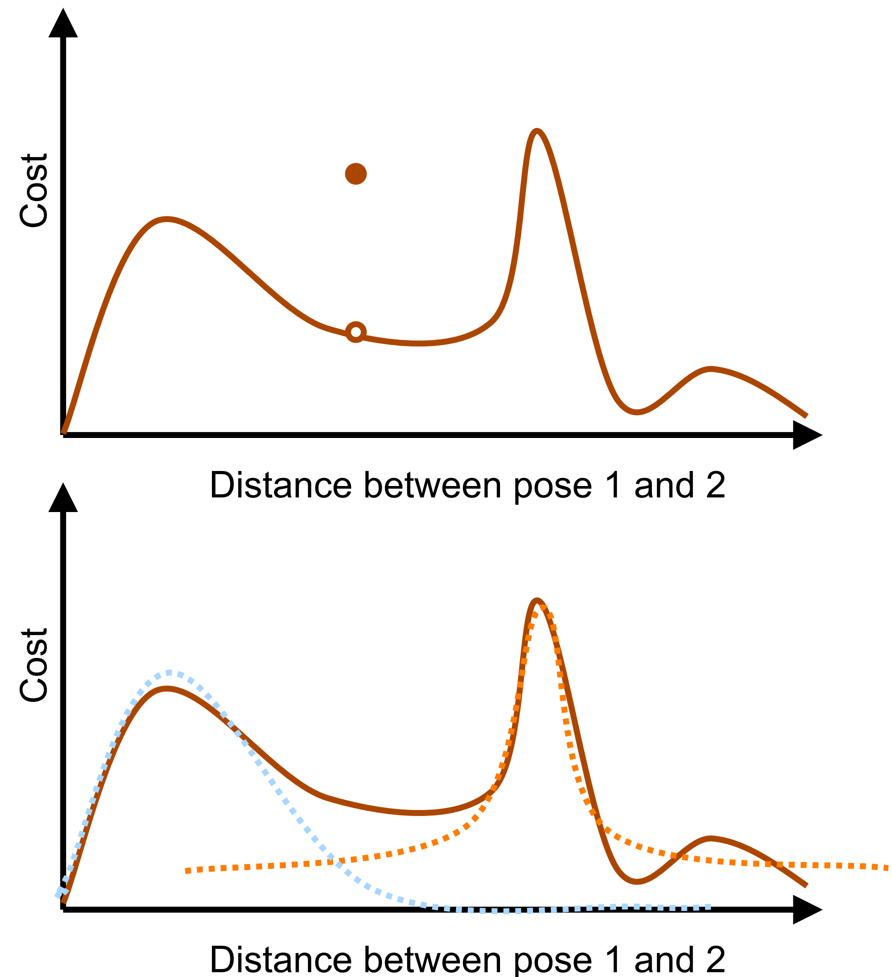
Data Association: Tick Marks

- Find a rotation that aligns the most tick marks…
  - Gives you data association for matched ticks
  - Gives you rigid body transform for the robot!

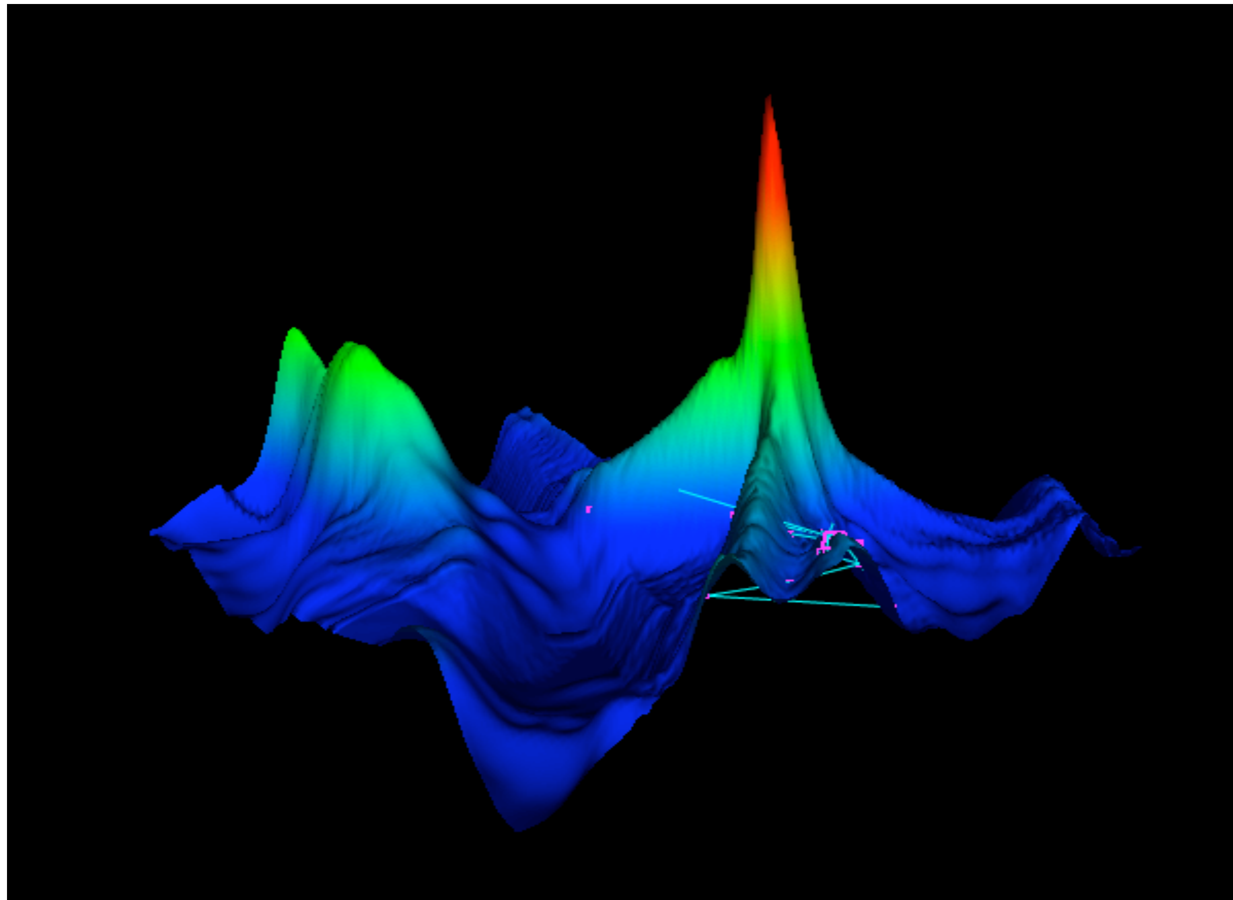


Metrical Map: Cost Function

- Cost function *could* be arbitrarily complicated
  - Optimization of these is intractable
- We can make a local approximation around *the current pose estimates*
  - Resembles the arbitrary cost function in that neighborhood
  - Typically Gaussian



Metrical Map: Real World Cost Function



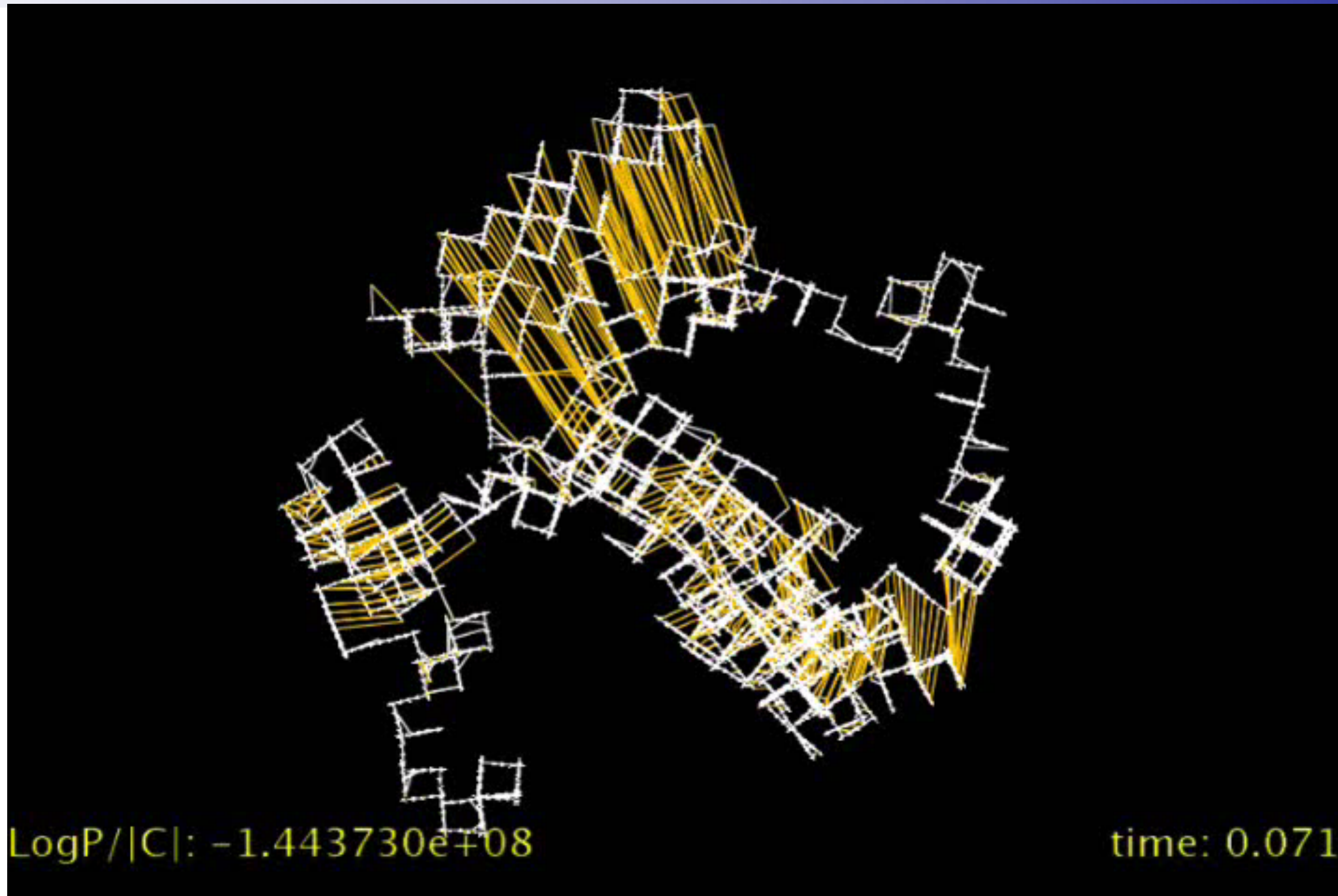
Cost function arising from aligning two LADAR scans

Nonlinear optimization: Relaxation

- Consider each pose/ feature:
  - Fix all others features/ poses
  - Solve for the position of the unknown pose
- Repeat many times
  - Will converge to minimum
  - Works well on small maps

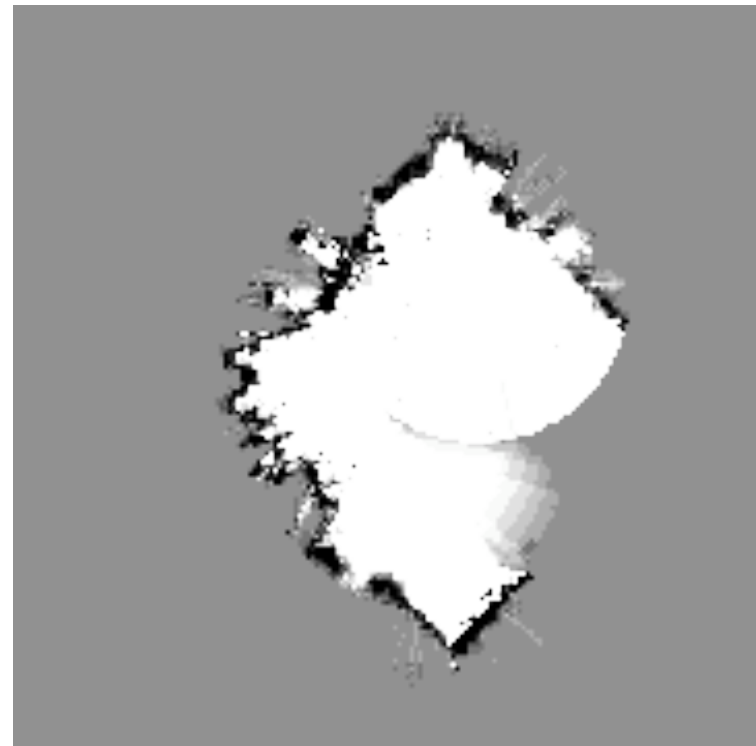
Pose/Feature Graph

Nonlinear Map Optimization



Occupancy Grids

- Divide the world into a grid
  - Each grid records whether there's something there or not
    - Usually as a probability
  - Use current robot position estimate to fill in squares according to sensor observations



Occupancy Grids

- Easy to generate, hard to maintain accuracy
  – Basically impossible to “undo” mistakes
- Convenient for high-quality path planning
- Relatively easy to tell how well you’re doing
  – Do your sensor observations agree with your map?

FastSLAM (Gridmap variant)

- Suppose you maintain a whole bunch of occupancy maps
  - Each assuming a slightly different robot trajectory
- When a map becomes inconsistent, throw it away.
- If you have enough occupancy maps, you’ll get a good map at the end.

Gridmap, a la MASLab

- Number of maps you need increases *exponentially* with distance travelled. (Rate constant related to odometry error)
- Build grid maps until odometry error becomes too large, then start a new map.
- Try to find old maps which contain data about your current position
  - Relocalization is usually hard, but you have unambiguous features to help.

Occupancy Grid: Path planning

- Use A* search
  - Finds optimal path (subject to grid resolution)
  - Large search space, but optimum answer is easy to find

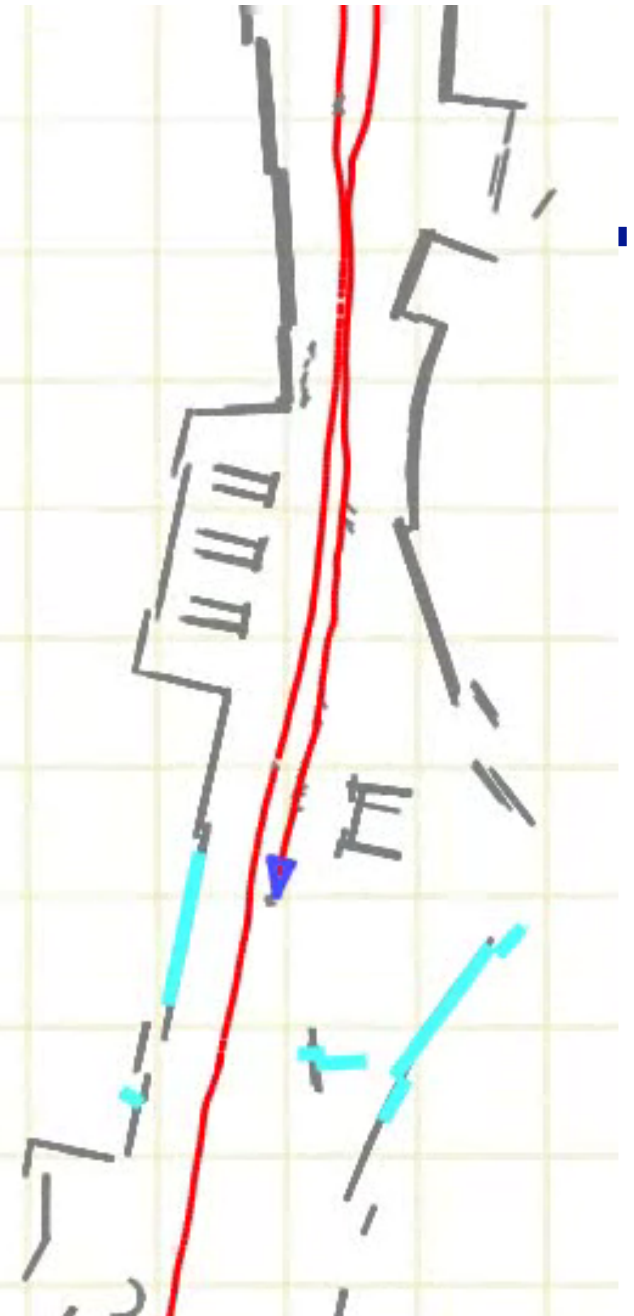
- search(start, end)
  - Initialize **paths** = set of all paths leading out of cell "start"
  - Loop:
    - let **p** be the best path in **paths**
      - Metric = distance of the path +
        straight-line distance from last cell in path to goal
    - if **p** reaches **end**, return **p**
    - Extend path **p** in all possible directions, adding those paths to **paths**

Occupancy Grid: Path planning

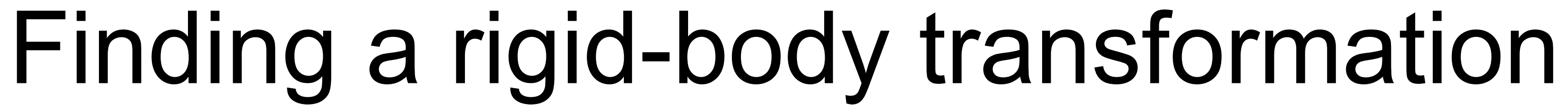
- How do we do path planning with EKFs?
- Easiest way is to rasterize an occupancy grid on demand
  - Either all walls/obstacles must be features themselves, *or*
  - Remember a local occupancy grid of where walls were at each pose.

Attack Plan

- Motivation and Terminology
- Mapping Methods
  - Topological
  - Metrical
- **Data Association**
- Sensor Ideas and Tips



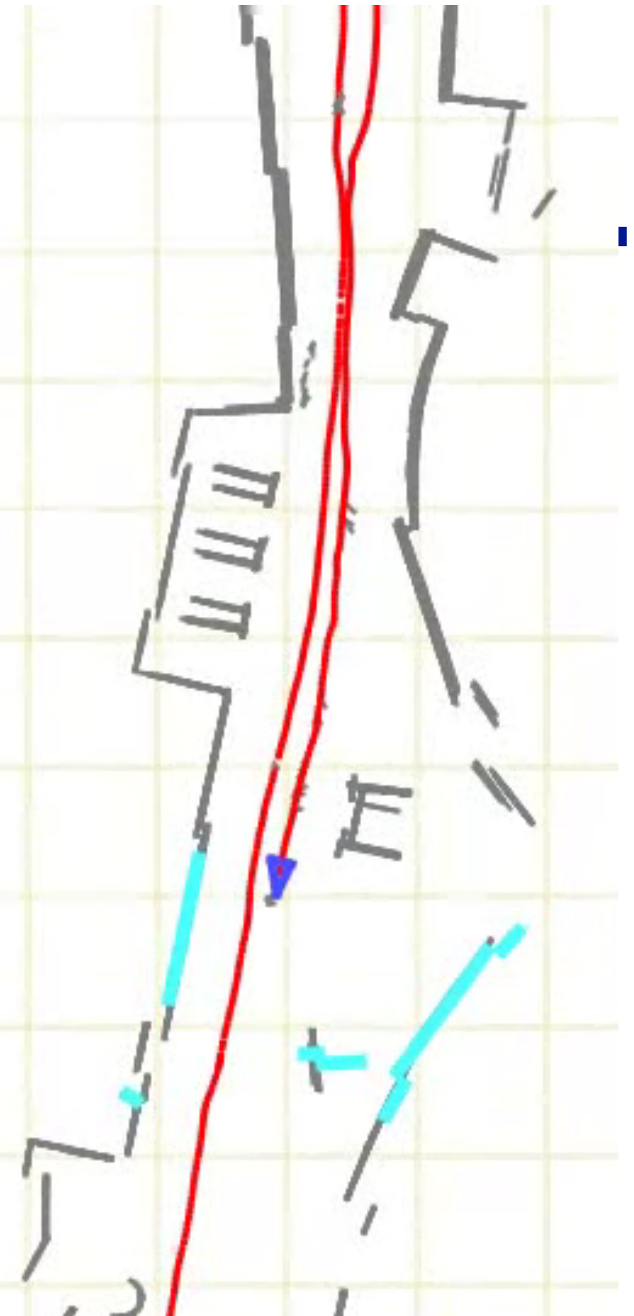
Finding a rigid-body transformation



- Method 1 (silly)
  - Search over all possible rigid-body transformations until you find one that works
    - Compare transformations using some "goodness" metric.
- Method 2 (smarter)
  - Pick two tick marks in both scene A and scene B
  - Compute the implied rigid body transformation, compute some "goodness" metric.
  - Repeat.
    - If there are N tick marks, M of which are in both scenes, how many trials do you need? Minimum: $(M/N)^2$
  - This method is called "RANSAC", RANdom SAmple Consenus

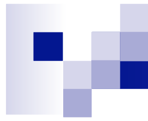
Attack Plan

- Motivation and Terminology
- Mapping Methods
  - Topological
  - Metrical
- Data Association
- **Sensor Ideas and Tips**



Debugging map-building algorithms

- You can't debug what you can't see.
- Produce a visualization of the map!
  - Metrical map: easy to draw
  - Topological map: draw the graph (using graphviz/dot?)
  - Display the graph via BotClient
- Write movement/sensor observations to a file to test mapping independently (and off-line)



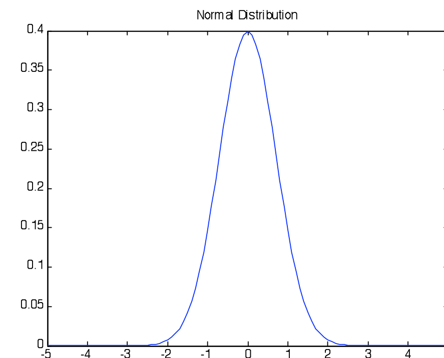
Today’s Lab Activities

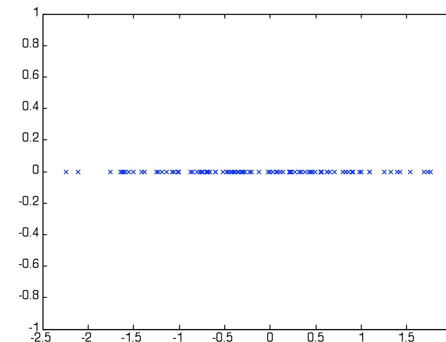
Bayesian Estimation

- Represent unknowns with probability densities
  - Often, we assume the densities are Gaussian

$$P(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x-\mu)^2/\sigma^2}$$

  - Or we represent arbitrary densities with particles
    - We won't cover this today





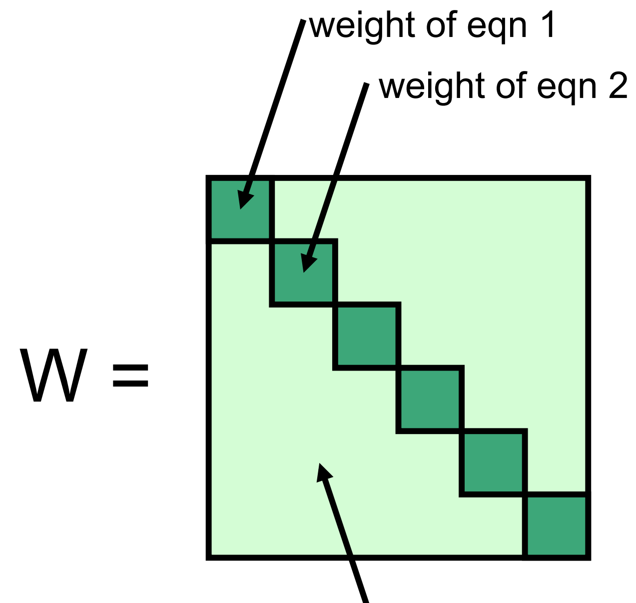
Metrical Map example

- Some constraints are better than others.
- Incorporate constraint "weights"
  - Weights are closely related to covariance:

    $$W = \Sigma^{-1}$$

  - Covariance of poses is:

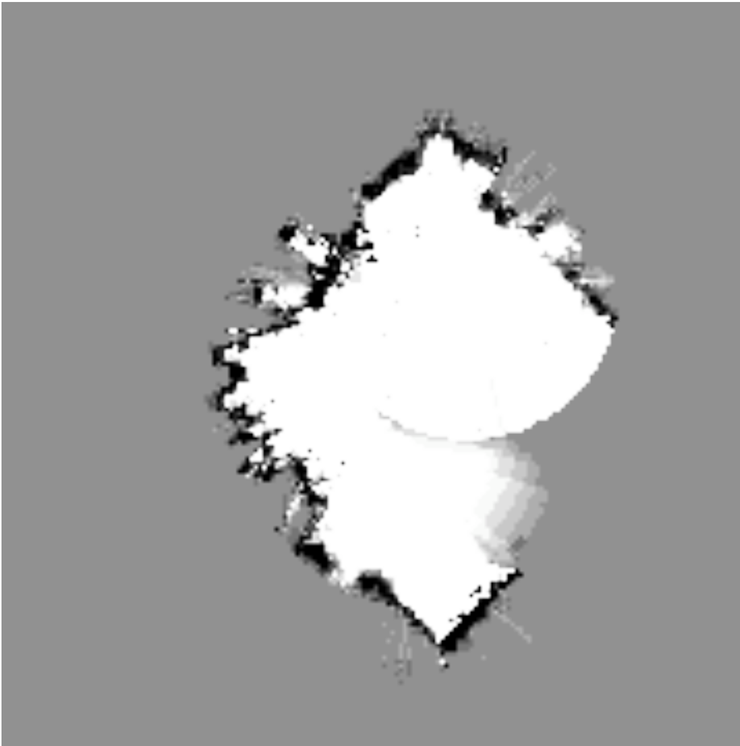
    $$A^TWA$$



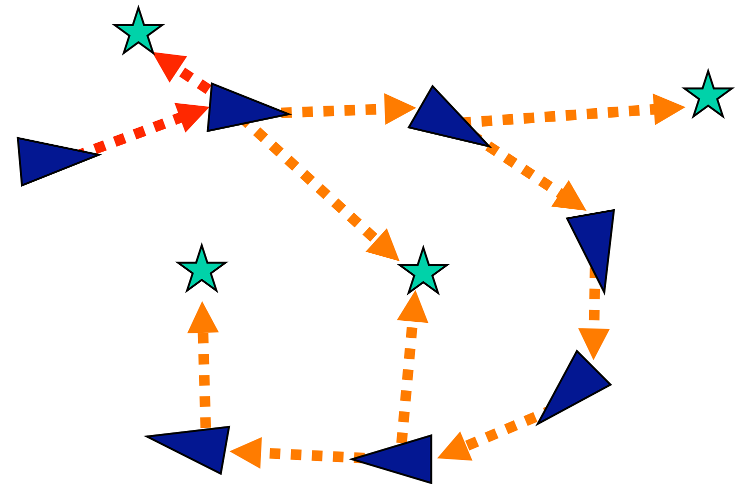
$$x = (A^TWA)^{-1}A^TWb$$

* Of course, "covariance" only makes good sense if we make a Gaussian assumption

Map representations



Occupancy Grid



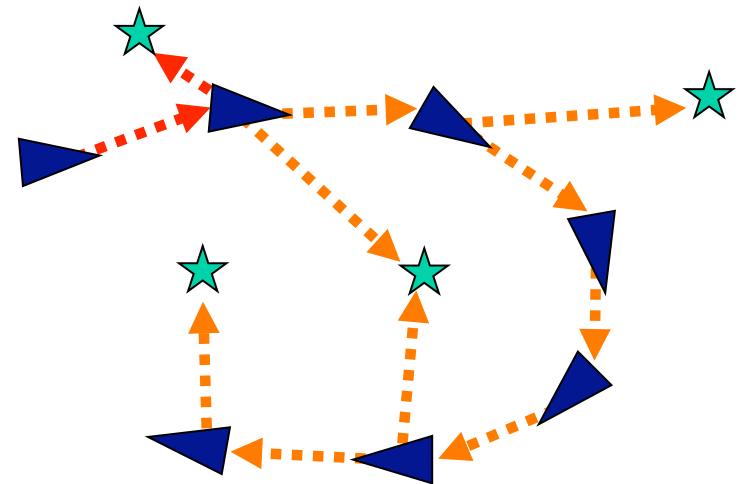
Pose/Feature Graph

Graph representations

- Occupancy Grids:
  - Useful when you have dense range information (LIDAR)
  - Hard to undo mistakes
- I don't recommend this…

Graph representations

- Pose/Feature graphs
  - **Metrical**
    - Edges contain relative position information
  - **Topological**
    - Edges imply “connectivity”
    - Sometimes contain “costs” too (maybe even distance)
- If you store ranging measurements at each pose, you can generate an occupancy grid *from* a pose graph



Pose/Feature Graph

Metrical Maps

- Advantages:
  - Optimal paths
  - Easier to visualize
  - Possible to distinguish different goals, use them as navigational features
  - Way cooler
- Disadvantages:
  - There's going to be some math.
    - *gasp* Partial derivatives!

State Correlation/Covariance

- We observe features relative to the robot's current position
  - Therefore, feature location estimates *covary* (or correlate) with robot pose.
- Why do we care?
  - We get the wrong answer if we don't consider correlations
  - Covariance is useful!

Metrical Map

- Once we've solved for the position of each pose, we can re-project the observations of obstacles made at each pose into a coherent map
- *That's why we kept track of the old poses, and why N grows!*

- What if we only want to estimate:
  - Positions of each goal
  - Positions of each barcode
  - *Current* position of the robot?

- The Kalman filter is our best choice now.
  - Almost the same math!
  - Not enough time to go into it: but slides are on wiki