

SLAM for Soar

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SLAM Theory / Code

- April Robotics Laboratory:
 - http://april.eecs.umich.edu/
- Presentation adapted from slides generously provided by Professor Edwin Olson
- Method similar to SLAM architecture used by Team Michigan in 2010 MAGIC Robotics Competition
- Radish: Robotics Data Set Repository
 - http://radish.sourceforge.net/

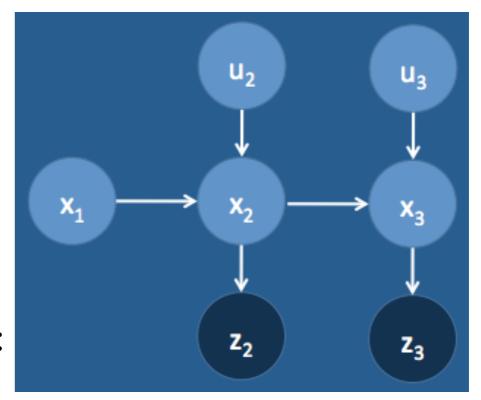




Simultaneous Localization and Mapping

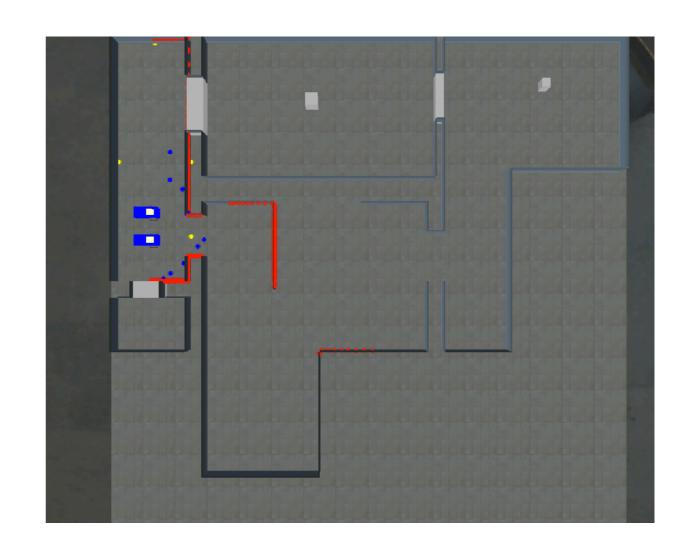
- While robot is exploring unknown environment:
 - * GIVEN: Robot's movement commands and observations of unknown environment
 - * ESTIMATE: Map of features and robot's path through environment
- Probabilistically motivated problem:
 - Errors within robot's movement and observations

$$p(s, f \mid u, z, d)$$



SLAM Motivation

- Soar Robot Project
 - Differentially driven robot utilizing LIDAR (LIght Detection And Ranging)
 - Encoders estimate robot's trajectory
- * What additional machinery is required to place agent in world?



Input Link ^io.input-link

Objects

^object ^id

^visible

 \wedge_{X}

^y

^distance

Arbitrary key-value properties

Examples:

- name: civ
- type: player

Waypoint System

^waypoints ^waypoint ^id

 \wedge_{X}

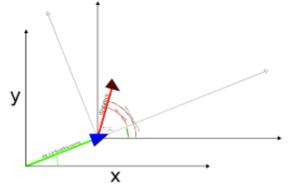
^y

^distance

^yaw

^relative-bearing

^abs-relative-bearing



Lidar

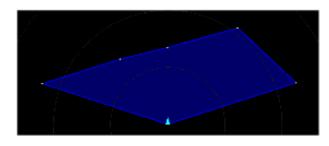
^lidar

^range

^id

^distance

^relative-bearing



About The Robot

^self

^name

^area

^headlight

^battery

^pose

 \wedge_{X}

^x-velocity

^y

^y-velocity

^yaw

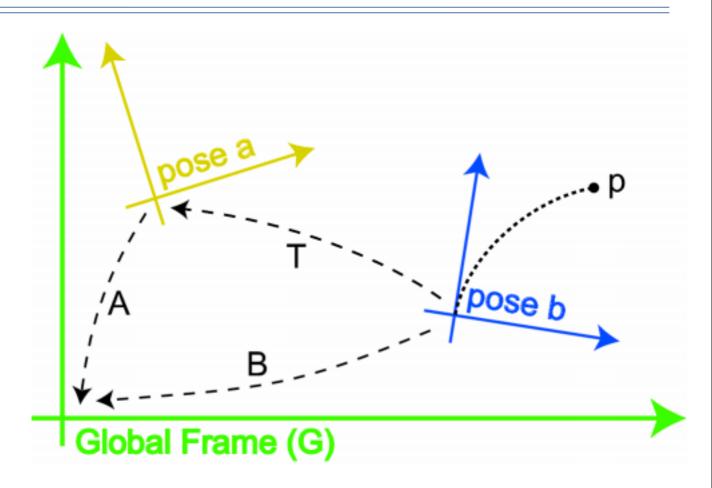
^yaw-velocity

Current Focus

Pose / Feature Graphs

- Poses and Features represented as 'Nodes'
- Connected by 'Edges' composed of Rigid Body Transformations
- * Additional observations create an overdetermined system
- Feature p in Global Frame:

$$p' = Ap$$
 $= ABp$



$$T = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) & \Delta x \\ \sin(\Delta\theta) & \cos(\Delta\theta) & \Delta y \\ 0 & 0 & 1 \end{bmatrix}$$

Non-Linear SLAM

- * Edge \longrightarrow Observation: $z_i = f_i(x)$
- * Observation Residual: $r_i = z_i f_i(x)$
- Scale Residual by Observation Confidence:

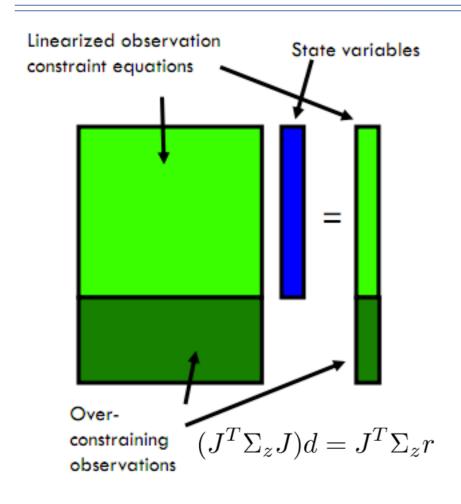
$$\chi_i^2 = (z_i - f_i(x))^T \Sigma_i^{-1} (z_i - f_i(x))$$

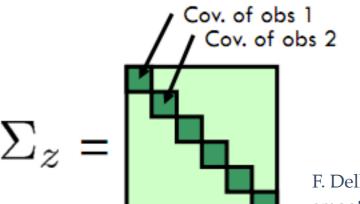
- Typical Observations != Linear
- Stack linearized observations using Jacobian:

$$\chi^2 \approx (Jd - r)^T \Sigma^{-1} (Jd - r)$$
 , where

- * *r* is the observation residual
- * d is the linearization residual $(x-x_0)$
- * Differentiate χ^2 with respect to d , solve for d which minimizes the χ^2 error

Square root SAM



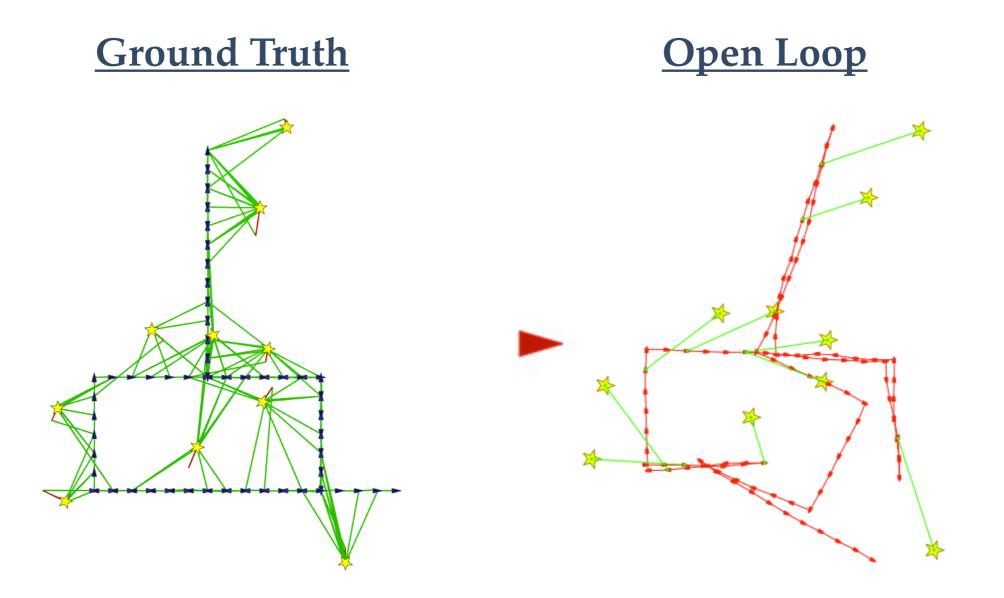


Naive Solution:

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

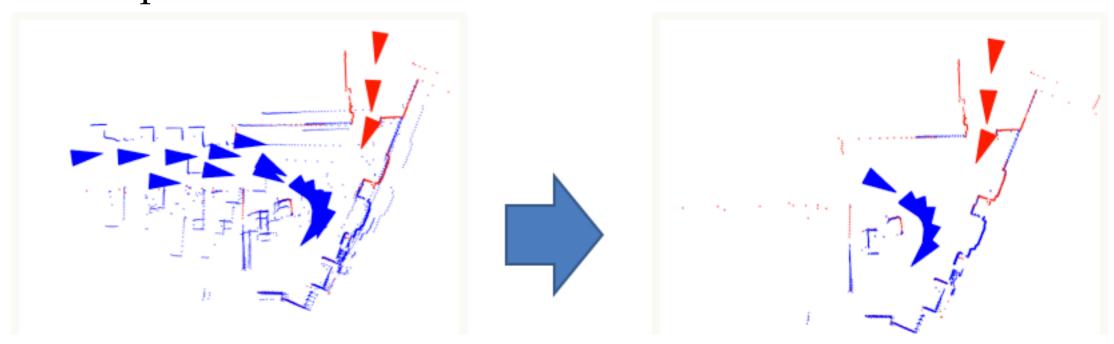
- * Typically impractical due to matrix inversion complexity $\sim O(N^3)$
 - Other SLAM methods attempt to approximate this
- Solution: Exploit sparsity within the information matrix
 - Reorder nodes to induce additional sparsity
 - Back solve using Cholesky decomposition

Square root SAM Demo



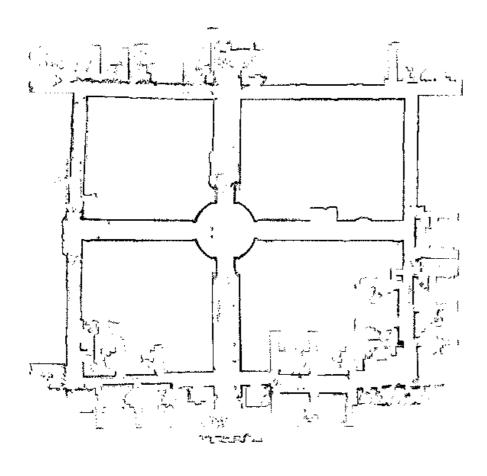
Loop Closure

- Using LIDAR to close the loop:
 - Determine if robot is in the location of a previous pose
 - Attempt to create RBT between two poses using their corresponding LIDAR scans
 - Resolution Scan Matching algorithm to align points of individual scans

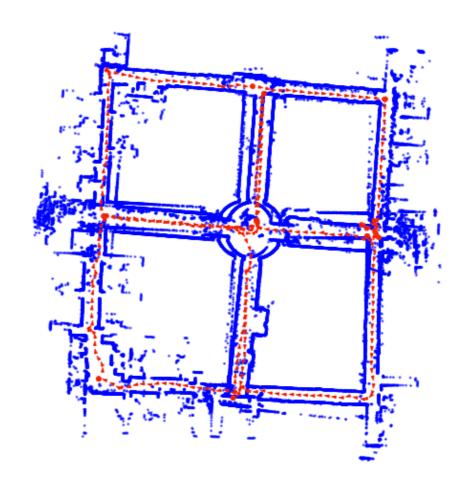


Full System Demo

Ground Truth



Open Loop



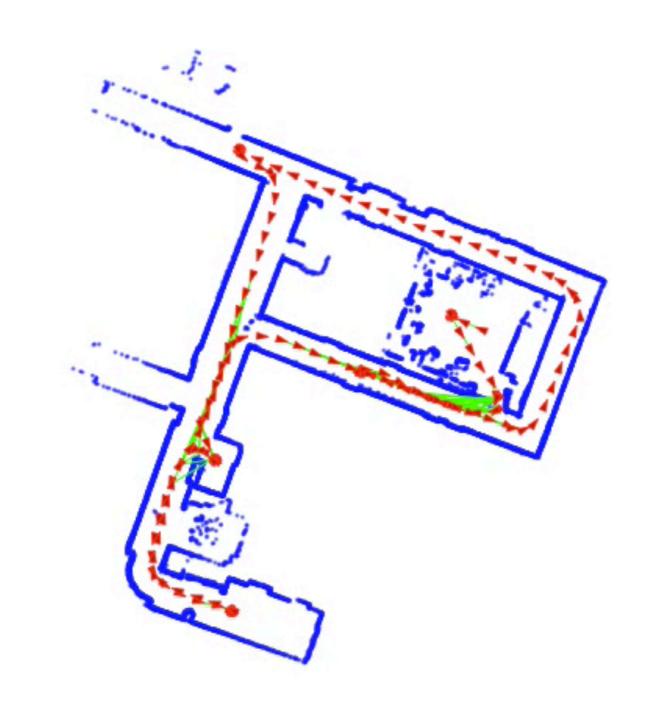
Evaluation

Nuggets

- Robust system capable of handling multiple environments
- Architecture supports the tracking of additional information
- System is sufficient to handle a minimal sensor suite

Coal

- Requires fine tuning of parameters depending upon sensors
- Have not implemented full system on robot / simulation
- * Still requires additional algorithms to provide information to input link



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