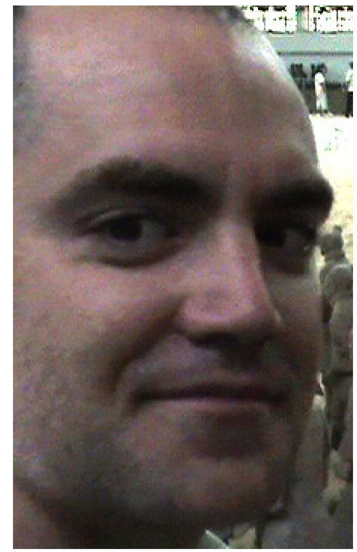
What Was That?

Discovering Natural Classes of Robot Sensory Experiences in Unstructured Environments





Department of Computer Science

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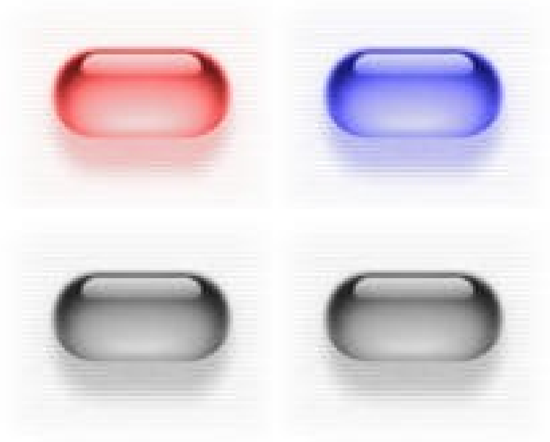
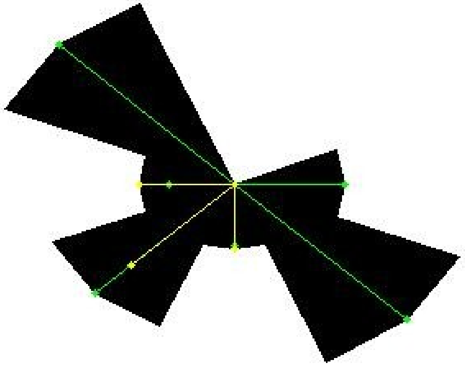
Motivation

- Robots and humans have different embodiments and sensor modalities.
- Robotic perception is different from that of humans.
- Human models of robot perception may be faulty or biased.
- Adopting data-driven techniques may avoid these biases.

Perception affects Decisions

- How to parameterize sensory experience w.r.t. the world
  - Distinguish physical space classes
- Cannot assume the robot can make human-distinguishable judgments

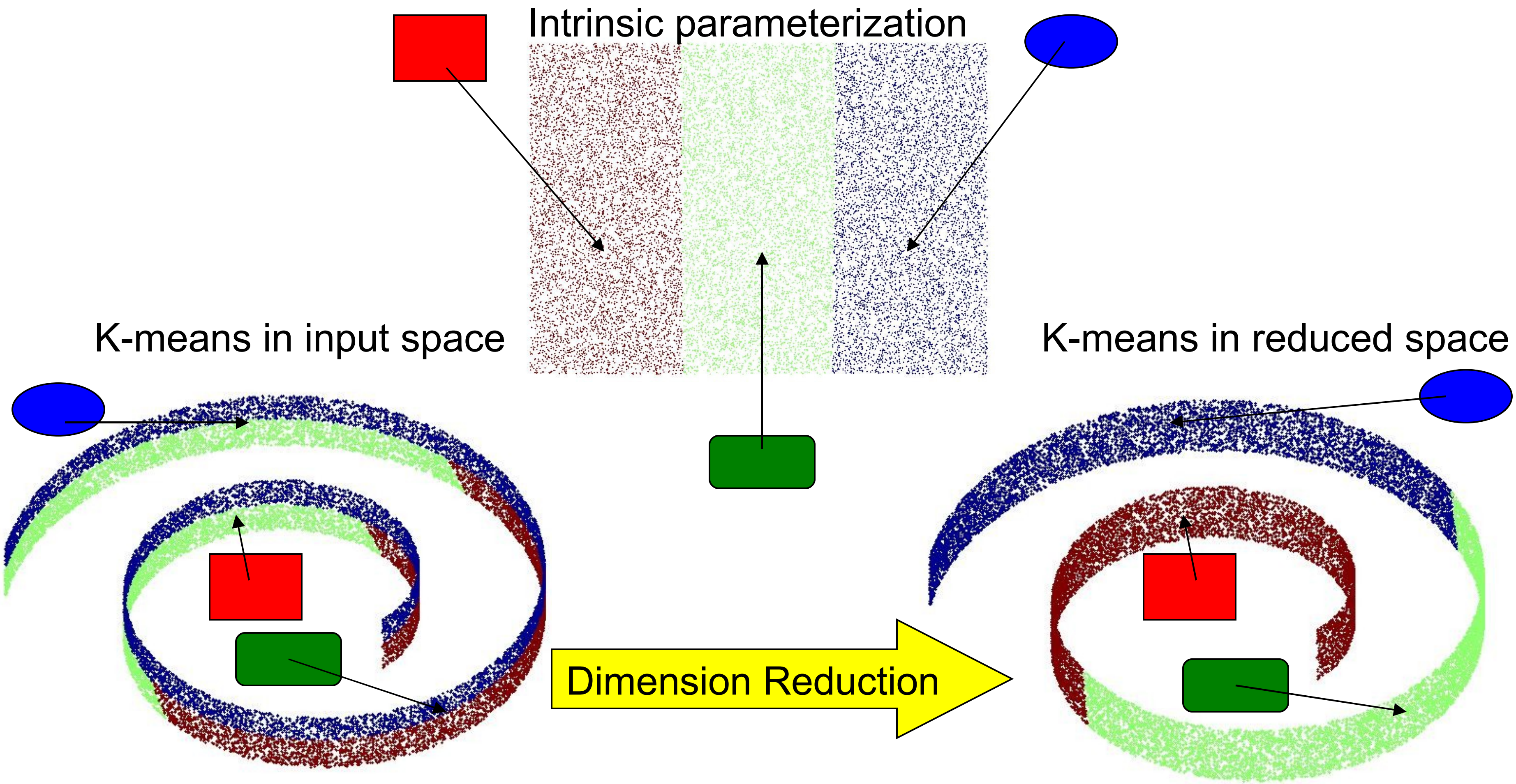




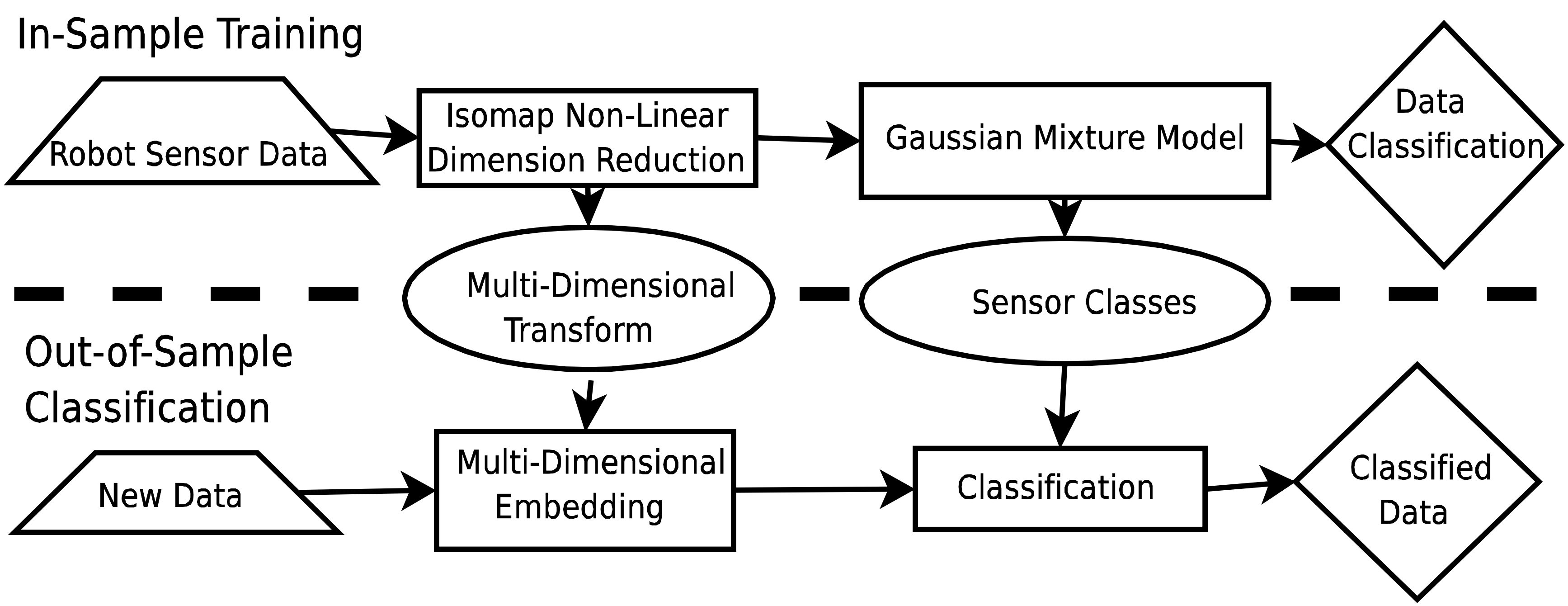
Data-Driven Discovery

- Learn what kinds (classes) of sensory experience exist and can be distinguished
- Only operate on sensory input
  - Could segment by hand and learn features (Supervised Learning)
- Goal: <u>consistent</u> labeling
  - Remove human bias
    - Not necessarily match human-made / model-based classes

Dimensionality of Data



Approach



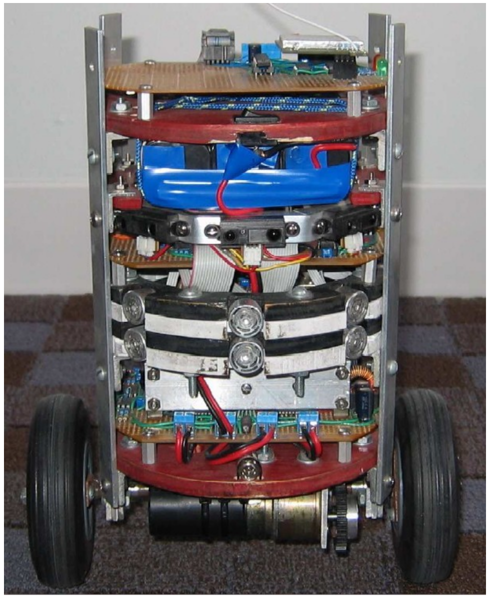
In-Sample Training
Robot Sensor Data
Isomap Non-Linear Dimension Reduction
Gaussian Mixture Model
Data Classification
Multi-Dimensional Transform
Sensor Classes
Out-of-Sample Classification
New Data
Multi-Dimensional Embedding
Classification
Classified Data

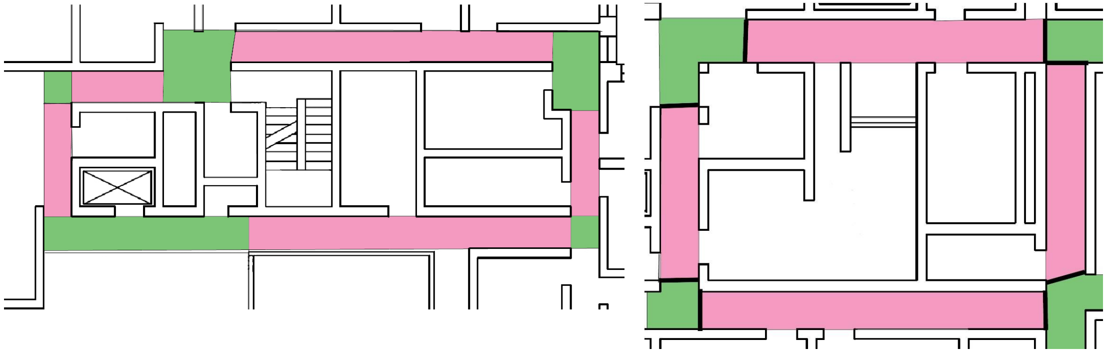
Non-Linear Dimension Reduction

- Isomap (Tenenbaum et al, 2000)
  – Compute geodesic distances between points through neighbors
  – Use Multi-Dimensional Scaling to embed into lower dimensions
- Cluster in embedded space
  – Gaussian Mixture Model

Setup

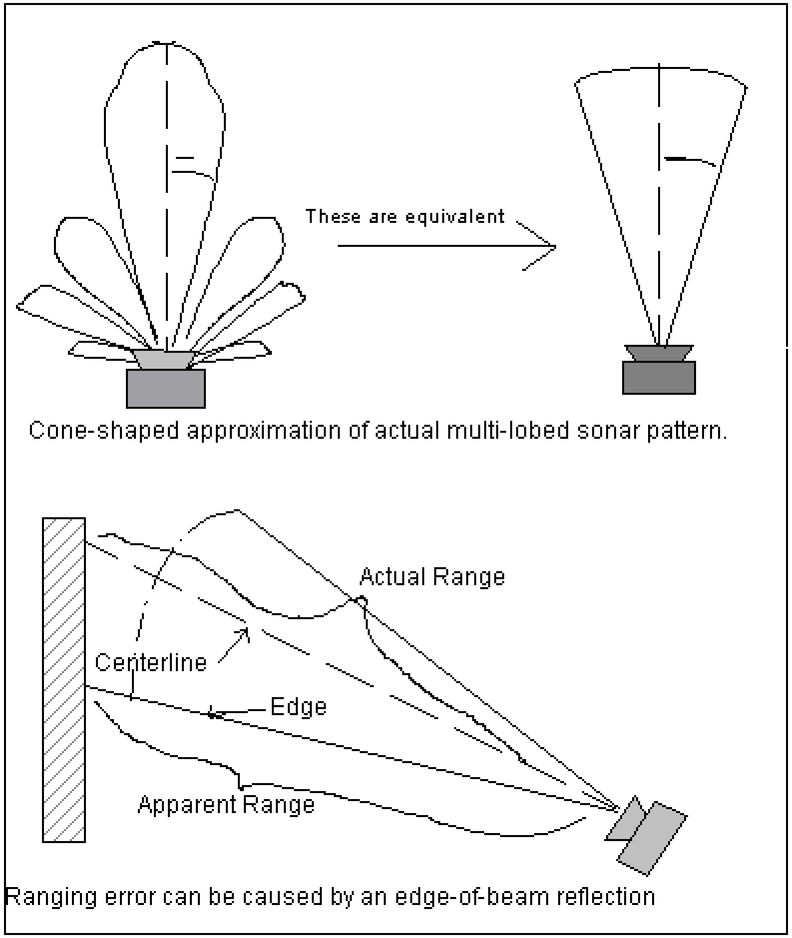
- Crunch – small inverted-pendulum robot, 8 sonar, 8 IR, 2 wheel encoders
- Office building environment
  - Could segment into 2 kinds



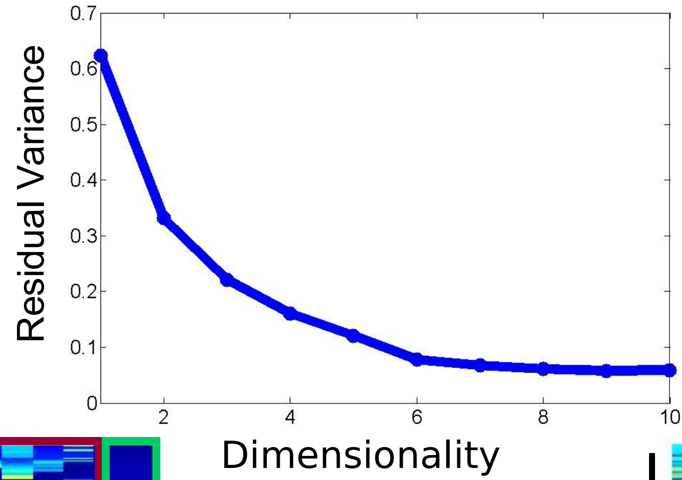


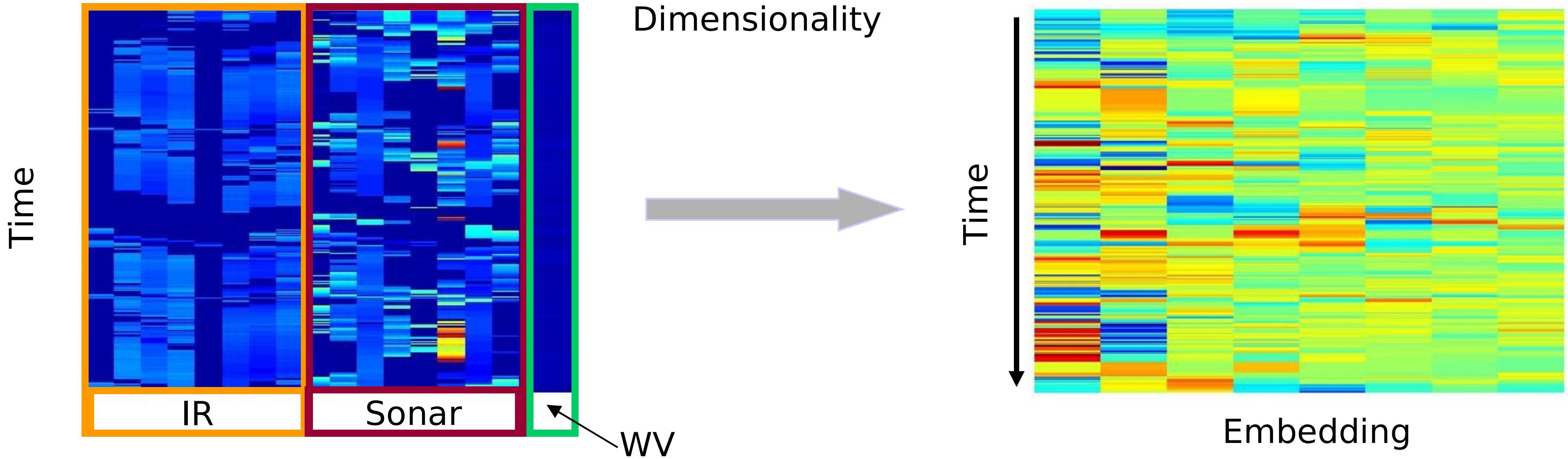
Training Data

- Time series of 18D readings from teleoperation of Crunch along the 4th floor loop. (~900 points)
- Sensors are: noisy, not equally functional and may not conform to models.



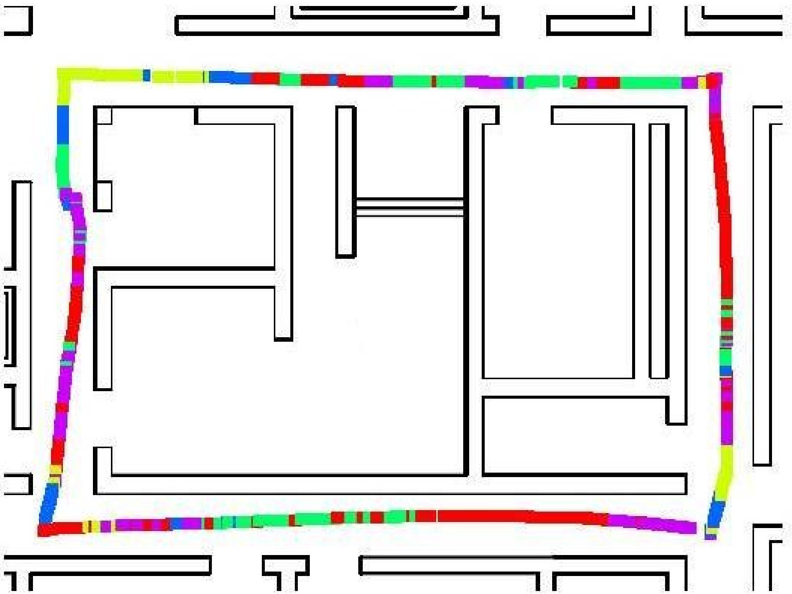
Dimension Reduction

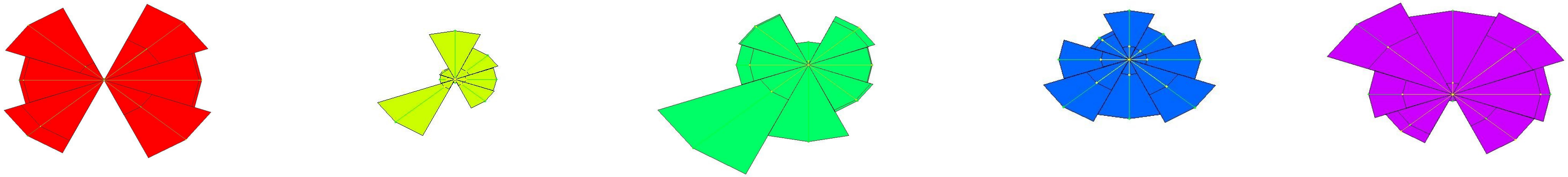




Clustering Results

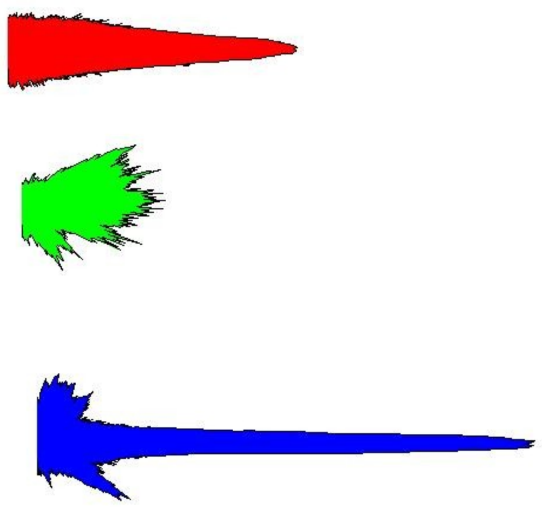
- We estimate 5 classes, overlay on registered odometry.
- Mean readings of each class





Lasers

- Processed SICK LMS laser data from Radish (FR079)
  - 180 degrees, 0.5 degree resolution, ~3000 points
- Conforms better to ray model



Test Data

- Out-Of-Sample extention (Bengio et al, 2004) allows new readings to be embedded and thereby classified using the GMM.
  - New Crunch data from same location
  - New Crunch data from different location

Video

Known Issues

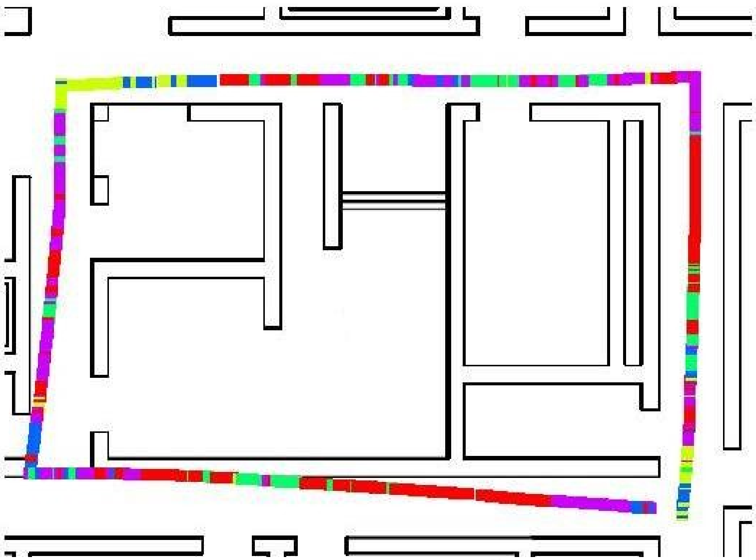
- Isomap
  - Computational limits
    - Landmarking issues
  - Assumes convexity of data
    - HLLE
  - Neighborhood selection
  - Sensor weighting
- Evaluation
  - Do not have access to ground truth
  - Rough consistency metric = ~60%
  - Real evaluations are applications

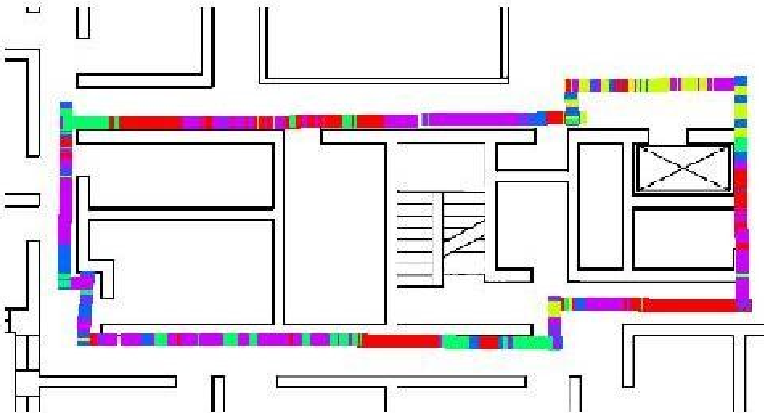
Future Work

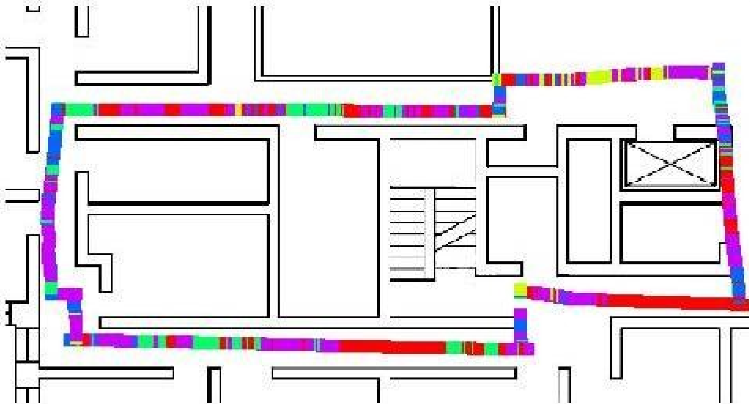
- Applications of classifier
  - Topological mapping
  - Sensor-motor connections
  - Pre/Post conditions for behaviors
- Leverage temporal information as well as spatial
- Bigger data sets
- Better evaluation

Questions?

Final Plots







Mathematical View

- Data: $D = \{\vec{x}_1, \ldots, \vec{x}_N\}$
- Geodesic Distance: $\tilde{D}(a,b) = \min_p \sum_i d(p_i, p_{i+1})$
- Embedding $\vec{e}_i = [\sqrt{\lambda_1} v_{1i}, \sqrt{\lambda_2} v_{2i}, \ldots, \sqrt{\lambda_k} v_{ki}]$
- New point $\vec{p}$
- New Embedding $e_k(\vec{p}) = \frac{1}{2\sqrt{\lambda_k}} \sum_i v_{ki}(E_{\vec{x}}[\tilde{D}^2(\vec{x}, \vec{x}_i)] + E_{\vec{x}'}[\tilde{D}^2(\vec{p}, \vec{x}')] - E_{\vec{x},\vec{x}'}[\tilde{D}^2(\vec{x}, \vec{x}')] - \tilde{D}^2(\vec{x}_i, \vec{p}))$