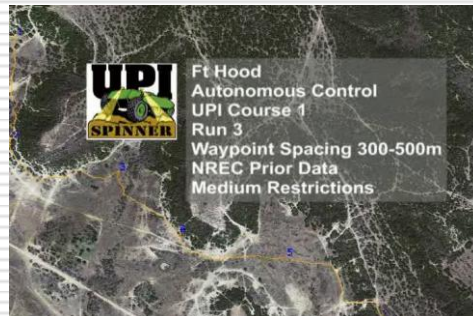


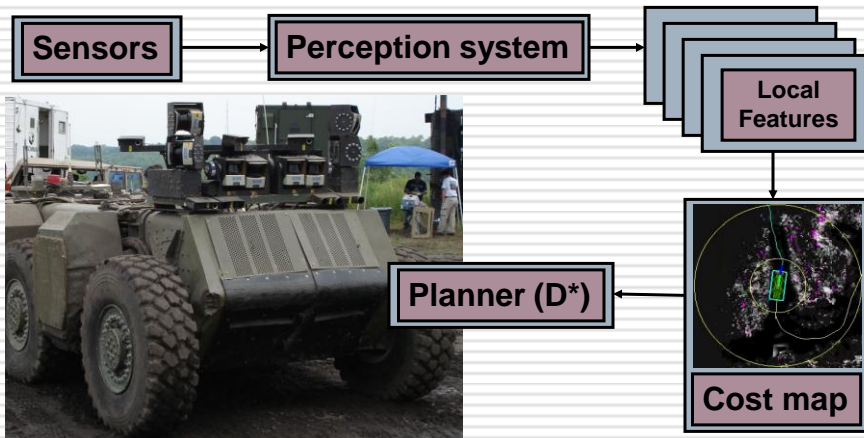
Self-Supervised Online Learning Approaches for Robot Navigation

16-831, Fall 2008
October 16

Mobile Robot Navigation



Local Perception System



3

Motivation

- Sensing range
 - Onboard perception system loses effectiveness at longer ranges (past 12-15 meters in this case)
 - Results in inefficient and often dangerous exploration



4

Motivation

- Sensing range
 - Onboard perception system loses effectiveness at longer ranges (past 12-15 meters in this case)
 - Results in inefficient and often dangerous exploration



5

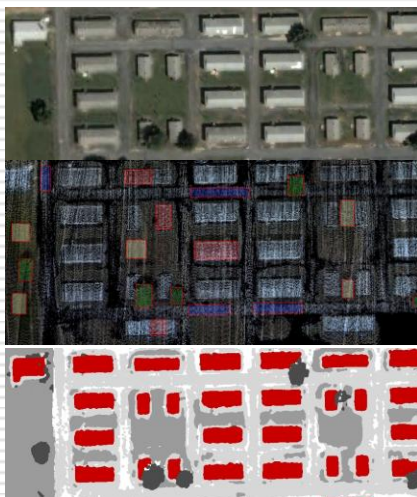
How to Improve

- Use overhead data (imagery, elevation, etc.)

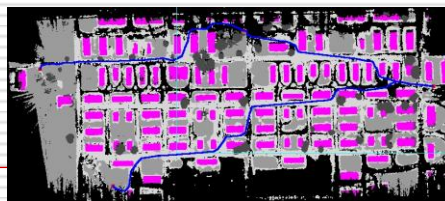


6

Hand-Train Overhead Interpreter

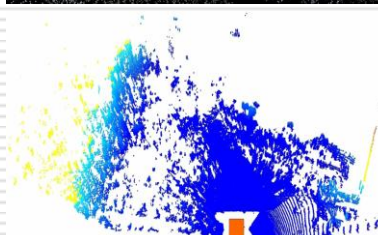


- Hand-train overhead classifier / cost predictor
- Apply to larger map
- Use resulting map for planning



How to Improve

- Use overhead data (imagery, elevation, etc.)
 - Difficult to interpret consistently
 - Variations in terrain, lighting, weather, time of gathering
- Extend the range of the perception system
 - Not enough data to accurately generate perception system's features
 - Can't estimate ground plane, inaccurate density, etc.
 - Features that are computable are difficult to interpret consistently



How to Improve

- ❑ Overhead data features
 - Color, texture, clustering, elevation, PCA, neighbor features, etc.
- ❑ Far-range sensor data features
 - Color, lidar point elevation spread / std, neighbor features, etc.
- ❑ How can we best use these potentially powerful, but difficult to generalize, features?

9

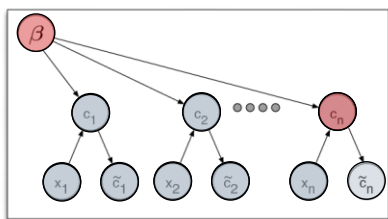
Scoped Learning

www.northsuburbanymca.org | 847.272.7250 | 2727 N. Elmhurst Ave. | Elmhurst, IL 60120

Family Services Director	Creative, energetic and enjoy working with people? Seeking director for program development, implementation and administration.
Massage Therapist - Male	The North Suburban YMCA is seeking a certified massage therapist to work part time in our men's program center. Flexible hours, y membership, on-site child care available if needed. Please contact Harlan Stirtchko by email or call at 847-272-7250.
Starbucks Server	Early day, evening and weekend shifts available for in-house cafe serving the Starbucks product line. An exciting opportunity and membership is included! Contact Sarah Tucker at 847-272-7250 x.213.
Teacher	Part-time 2-6 pm, Monday through Friday. Minimum requirements are 60 college credit hours in Early Childhood or Education or similar subject. At least one year experience working with 2-5 year olds. Contact Helen at (847) 272-7250 x222 and fax resume to (847) 272-7587.
Art Coordinator	Creative? Enjoy working with children? The North suburban Y is looking for an art coordinator for the summer. Call Jane at (847)272-7250 for more information.
Teachers	Seeking part-time early childhood teachers for summer or all year. 2-3 mornings per week from 9am-11:15am. Free child care on-site while you work. Free YMCA membership.
Customer Service Rep	OVERQUALIFIED APPLY HERE! Hone your skills by working in a friendly environment. The front desk is looking for part time staff to work flexible shifts for early weekday mornings, day and evening shifts. Benefits include YMCA membership and babysitting during your shift. Please contact Sarah Tucker or Cheryl Stewart at (847) 272-7250 x.213.
Lifeguards	Love to swim? Love kids? Put the two together and make a difference. The North Suburban YMCA is looking for qualified and experienced swim instructors and lifeguards. Will train the right candidate.

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The Algorithm



x_i - computed locale-specific features
 c_i - true traversal costs
 \tilde{c}_i - estimates generated by perception system
 β - captures relationship between x_i and c_i

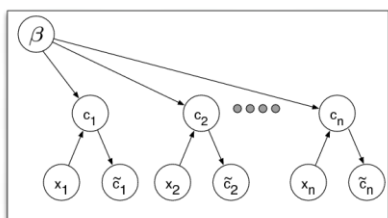
$$E[c_{n+1}] = \beta^T x_{n+1}$$

$$p(c_{n+1} | \tilde{c}_{1..n}, x_{1..n+1})$$

- Model the relationship between these features and measured traversal cost in a Bayesian probabilistic framework
 - Online Bayesian Linear Regression
- Relate multiple data sources with different "scope" to each other

Blei, '02 11

The Algorithm



x_i - computed locale-specific features
 c_i - true traversal costs
 \tilde{c}_i - estimates generated by perception system
 β - captures relationship between x_i and c_i

$$E[c_{n+1}] = \beta^T x$$

$$p(c_{n+1} | \tilde{c}_{1..n}, x_{1..n+1})$$

$$p(\beta | \tilde{c}_{1..n}, x_{1..n}) \propto p(\tilde{c}_{1..n} | \beta, x_{1..n}) p(\beta)$$

- Initialize the distribution to the prior distribution $p(\beta)$
- We want to compute $p(\beta | \tilde{c}_i, x_i, D)$
 - For every training example (x_i, \tilde{c}_i) , multiply the distribution by $p(\tilde{c}_i | \beta, x_i)$
- By computing $p(\beta | \tilde{c}_i, x_i, D)$, we are performing self-supervised learning using a Bayesian linear regression model

$$P \leftarrow P + \frac{x_i x_i^T}{\sigma^2} \quad J \leftarrow J + \frac{\tilde{c}_i x_i}{\sigma^2}$$

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The Algorithm



- Learn to interpret these locale-specific features by taking advantage of the globally interpretable features from the perception system



The Algorithm



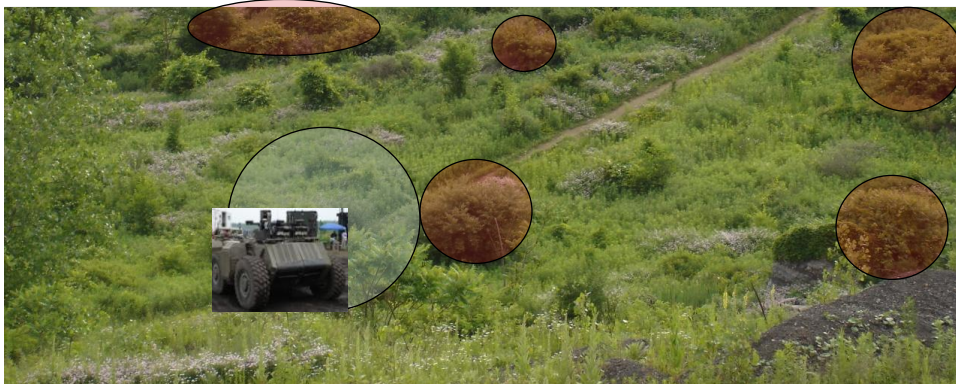
- Learn to interpret these locale-specific features by taking advantage of the globally interpretable features from the perception system



The Algorithm



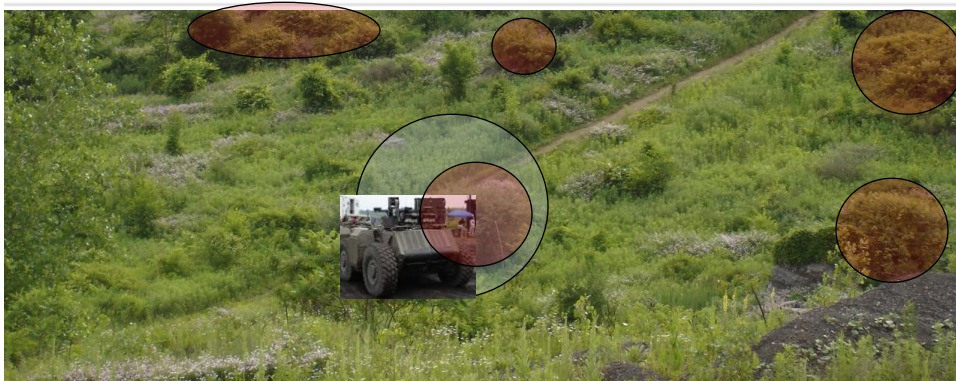
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The Algorithm



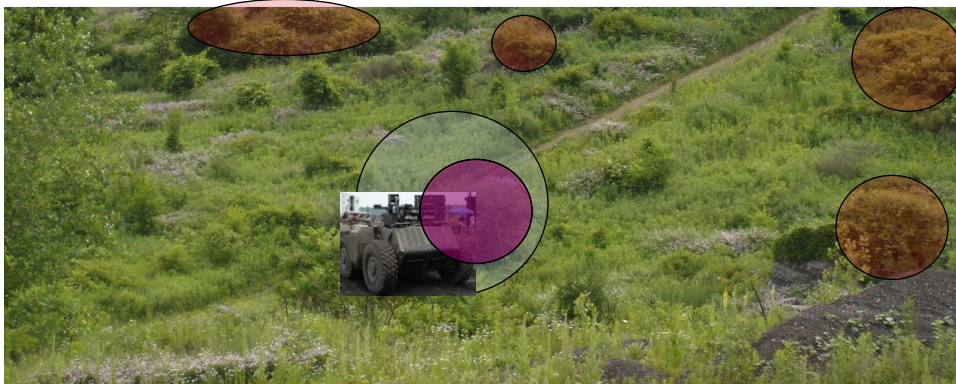
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The Algorithm



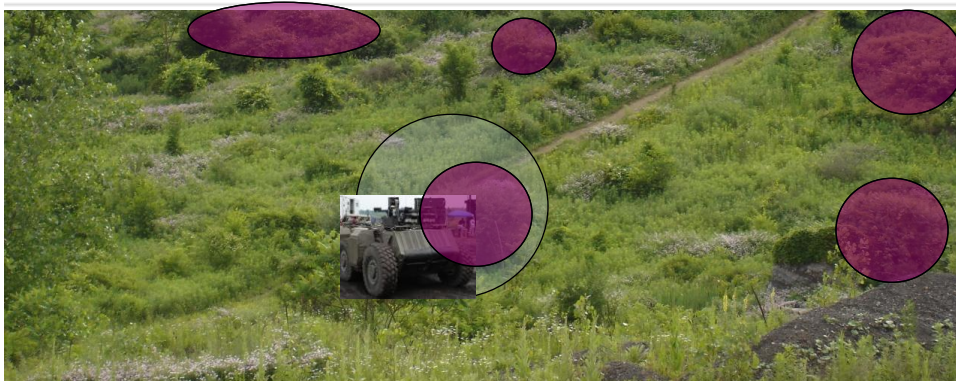
- Learn to interpret these locale-specific features by taking advantage of the globally interpretable features from the perception system



The Algorithm



- Learn to interpret these locale-specific features by taking advantage of the globally interpretable features from the perception system



Results

- Overhead Online Learning
 - Online use
 - Offline use
- Far-Range Online Learning

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Results

- Overhead Online Learning
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 - Offline use
- Far-Range Online Learning

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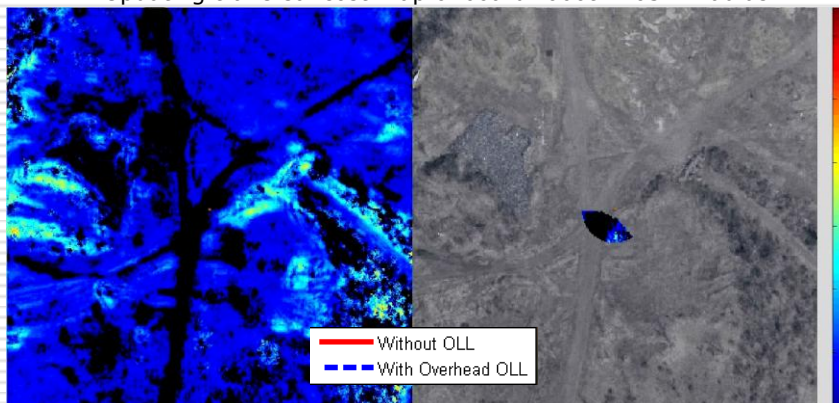
Results

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21

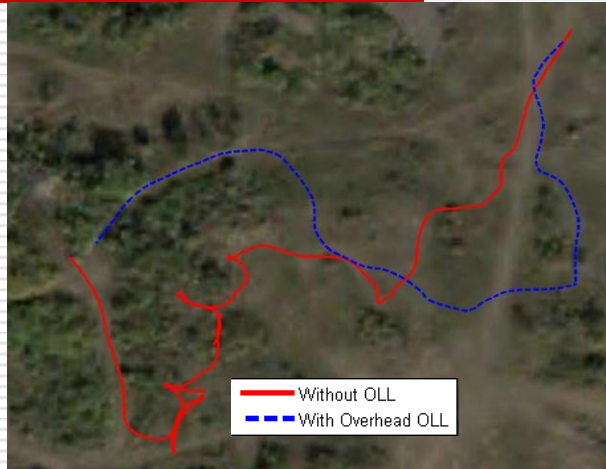
Overhead Online Learning

Using features from 40cm color imagery and elevation data
Updating traversal cost map onboard robot in 65 m radius



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Overhead Online Learning



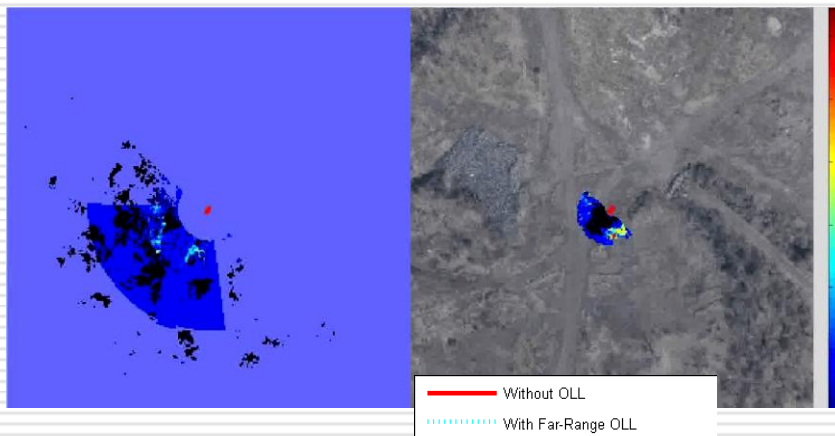
23

Results

- Overhead Online Learning
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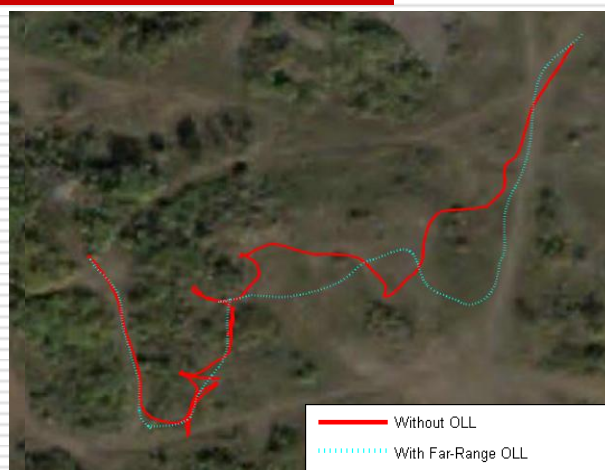
24

Far-Range Online Learning



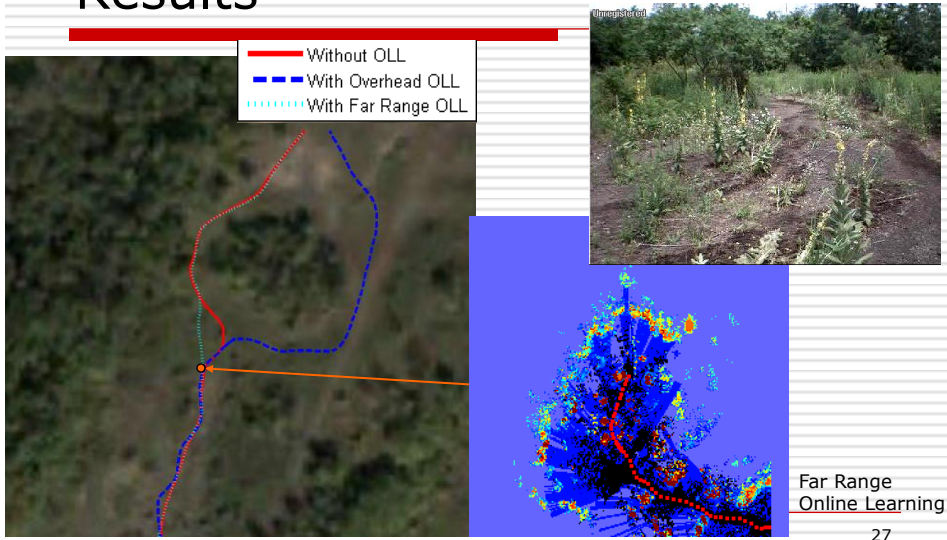
25

Far-Range Online Learning

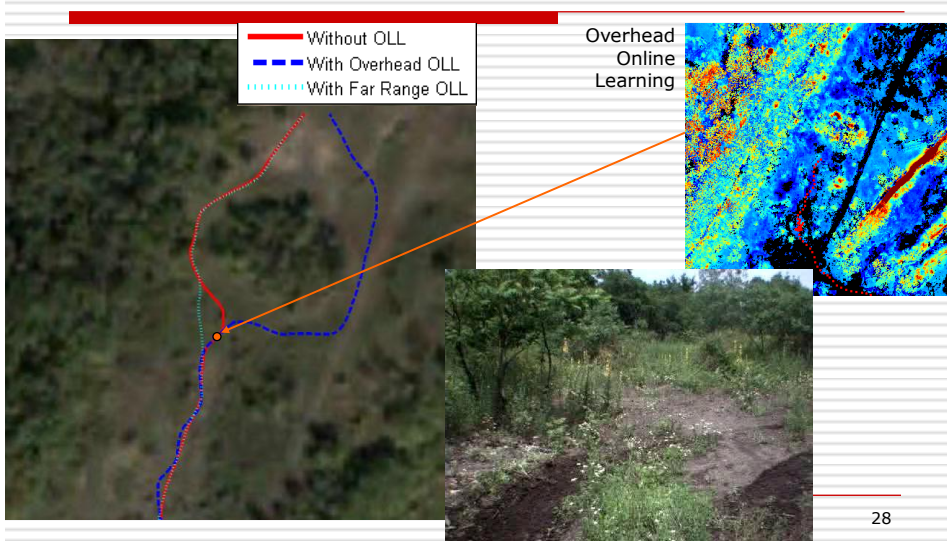


26

Results



Results



Results

- Overhead Online Learning
 - Online use
 - Offline use
- Far-Range Online Learning

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Overhead Online Learning (Offline)

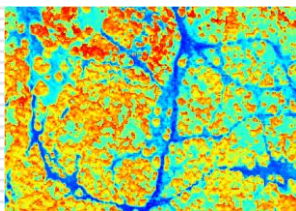
2000m x 750m



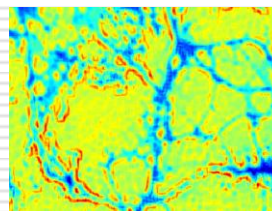
Training course

30

Overhead Online Learning (Offline)



Using 35cm color imagery data

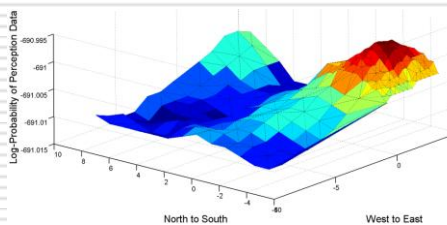
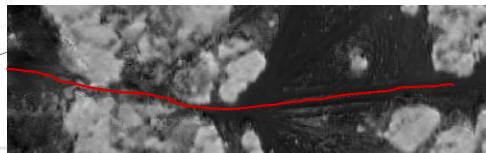
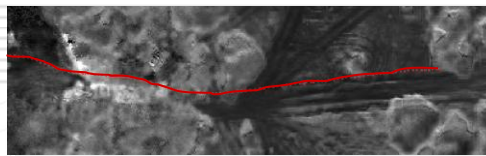


Using 1m black and white imagery data

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Overhead Online Learning (Offline)

- Data alignment
 - Use $p(\tilde{c}_1, \dots, \tilde{c}_n)$ to detect most likely map alignment
 - Use alignment with the highest average log probability over all examples seen



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Additional Benefits

- Reversible learning
- Confidence-rated predictions

33

Reversible Learning

- Multiple estimates of single quantity

- Receive example (x_i, \tilde{c}_i)

$$P \leftarrow P + \frac{x_i x_i^T}{\sigma^2} \quad J \leftarrow J + \frac{\tilde{c}_i x_i}{\sigma^2}$$

- Receive lower variance estimate \tilde{c}'_i

$$J \leftarrow J - \frac{\tilde{c}_i x_i}{\sigma^2} + \frac{\tilde{c}'_i x_i}{\sigma^2}$$

- β always takes into account only best estimates available for all examples

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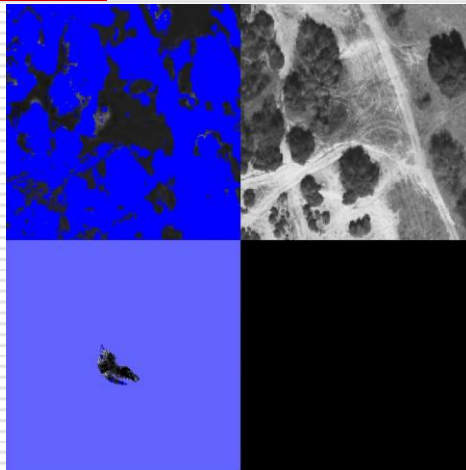
Additional Benefits

- Reversible learning
- Confidence-rated predictions

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Confidence-rated predictions

- Use variance estimate (HW3!) provided by algorithm for the probability of each estimate as measure of confidence
- "Surprise" at seeing set of features



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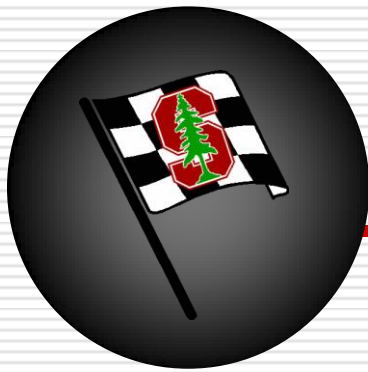
Far-Range Online Learning with Velodine

Movie...

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Questions?





A Self-Supervised Terrain Roughness Estimator for Off-Road Autonomous Driving

David Stavens and Sebastian Thrun
Stanford Artificial Intelligence Lab

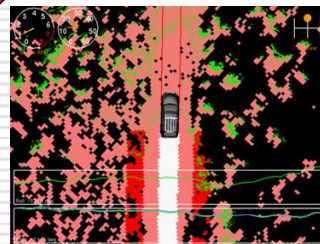
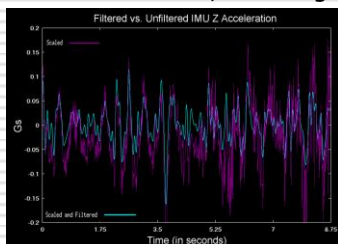
“Combines” strengths of multiple sensors.



Ultra-Precise, No Range



Precise, Long Range



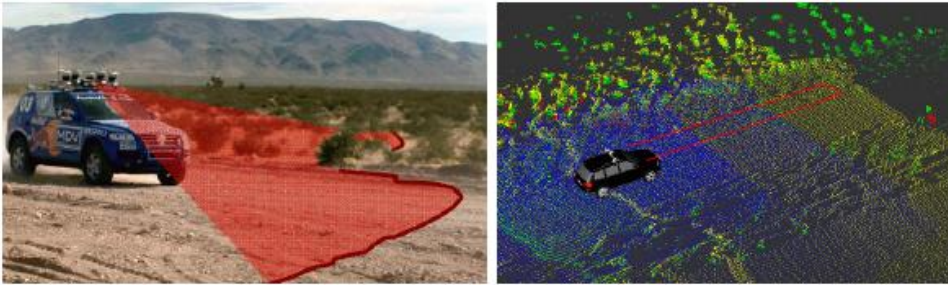
Velocity Planning for DGC 2005

- Mobile robotics traditionally focuses on steering.
 - But *speed* is also important.
 - Beyond stopping distance and lateral maneuverability.
 - Stanley adapted its speed to terrain conditions, minimizing shock:
 - Increases electrical and mechanical reliability.
 - Mitigates pose error for laser projection.
 - Increases traction for improved maneuvers.
 - Correlated with slowing on “hard” terrain.
-

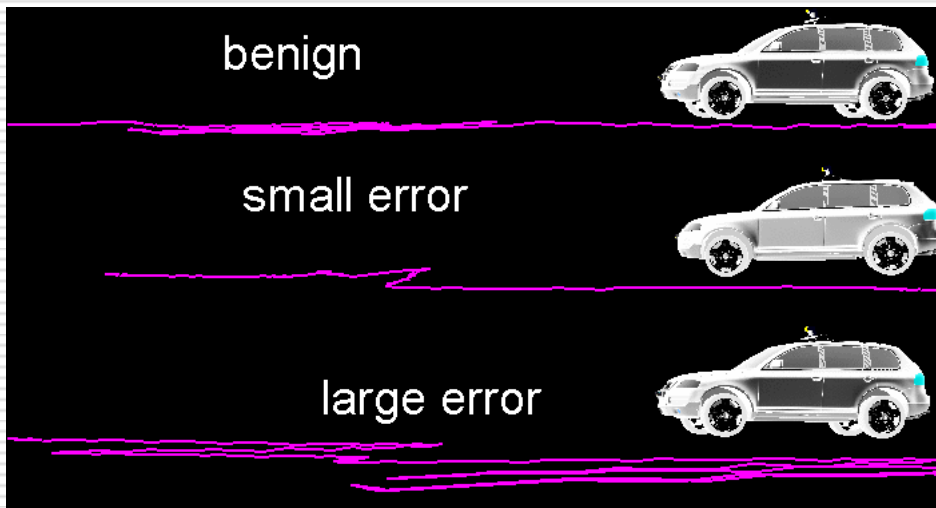
Reactive Approach (used during DGC)

- Simple three state algorithm:
 - Drive at speed limit until shock threshold exceeded.
 - Slow to bring the vehicle within the shock threshold.
 - Uses approx. linear relationship between shock and speed.
 - Accelerate back to the speed limit.
-

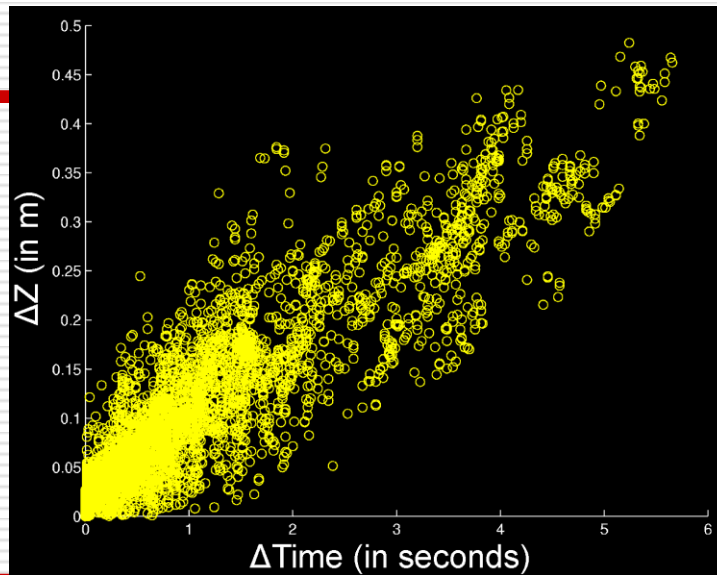
Acquiring a 3D Point Cloud



Movie...



Goal: know amount of error that is expected so that actual rough terrain or obstacles may be better identified.



More than Δt

- "Spread" of plot implies more factors than Δt .
- Also related to:
 - Amount/rate of pitching.
 - Distance between the two scans.

Comparing Two Laser Points

$$\text{Uncertainty} = \Delta_{\text{pair}} =$$

$$\alpha_1 | \Delta z |^{\alpha_2} -$$

$$\alpha_3 | \Delta t |^{\alpha_4} -$$

$$\alpha_5 | \text{xy distance} |^{\alpha_6} -$$

$$\alpha_7 | \text{dpitch}_1 |^{\alpha_8} - \alpha_7 | \text{dpitch}_2 |^{\alpha_8} -$$

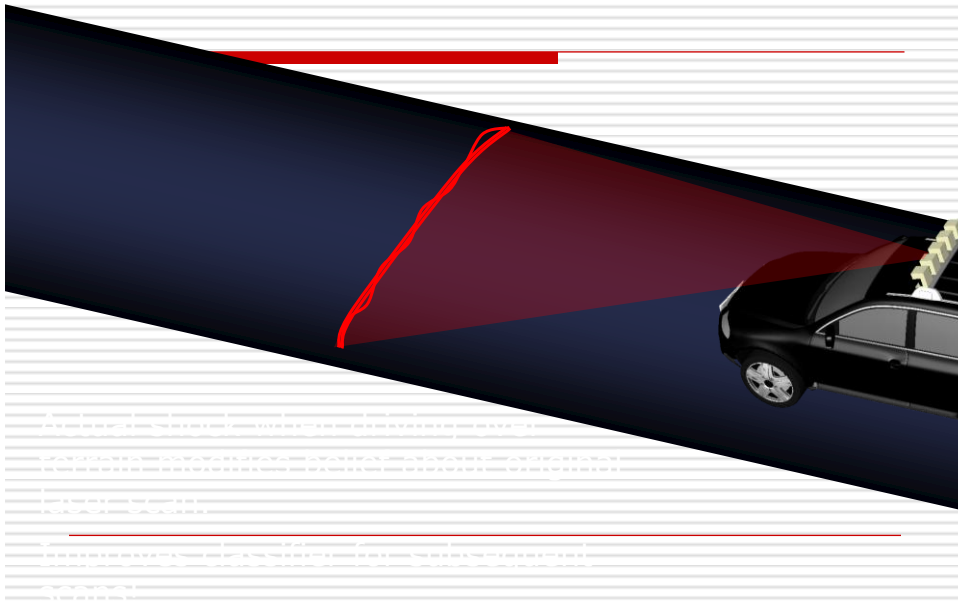
$$\alpha_9 | \text{droll}_1 |^{\alpha_{10}} - \alpha_9 | \text{droll}_2 |^{\alpha_{10}}$$

- Seven Features: Δz , Δt , xy distance, dpitches, drolls
- 10 Parameters: $\alpha_1 \alpha_2 \dots \alpha_{10}$ (generated with self-supervised learning)

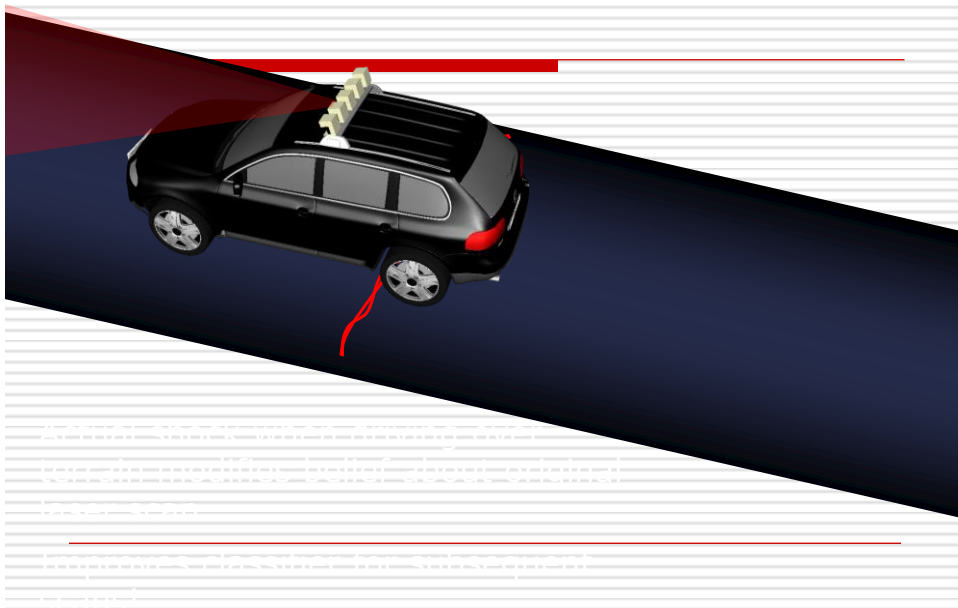
Estimate Roughness

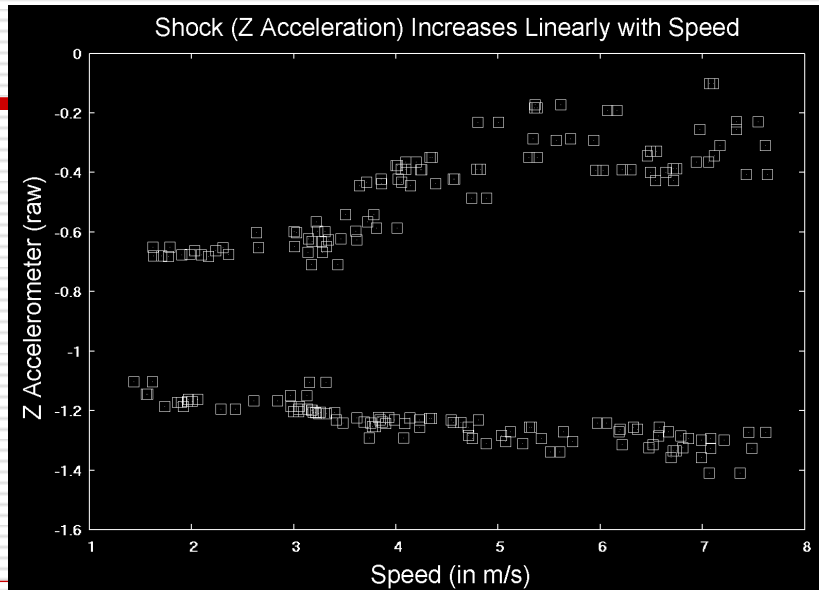
- Combine points in estimated future locations of wheels to estimate a roughness score, R , for terrain patch.
- But how do we assign target values to R ?

Self-Supervised Learning



Self-Supervised Learning





Mapping from R to Shock

Learn a simple suspension model
in parallel with the classifier:

$$R_{\text{combined}} = R_{\text{left}}^{\alpha_{11}} + R_{\text{right}}^{\alpha_{11}}$$

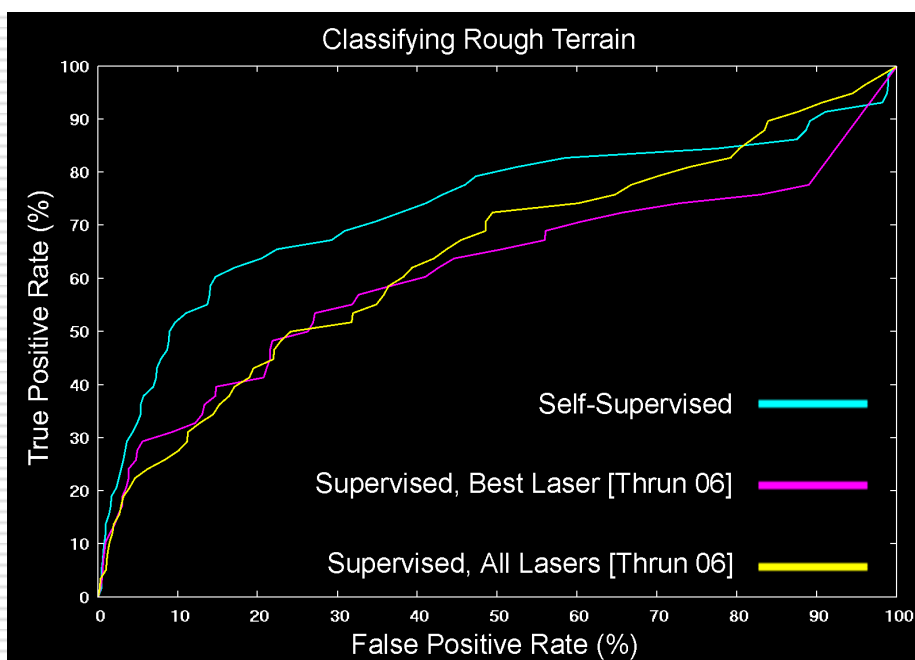
R_{left} and R_{right} is for the terrain
under each wheel.

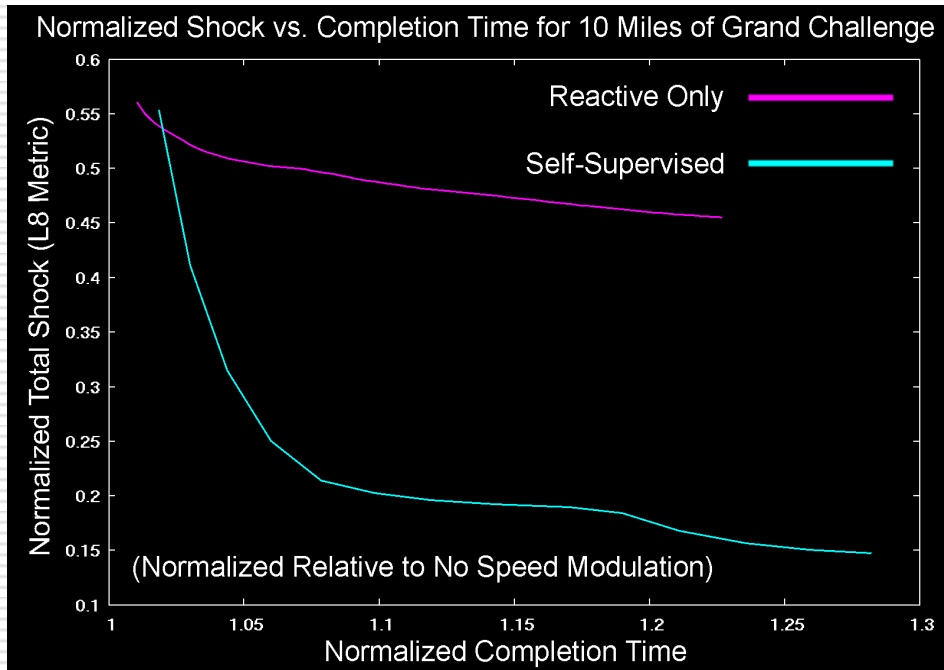
Learning Parameters

- T_p = true positive rate
- F_p = false positive rate

- Maximize $T_p - \lambda F_p$
 - Used $\lambda = 5$ to minimize false positives
- Optimized through coordinate ascent
 - Greedily optimize each parameter individually, decreasing learning rate each cycle by factor of 2.

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Self-Supervised Monocular Road Detection in Desert Terrain

Hendrik Dahlkamp, Adrian Kaehler,
David Stavens, Sebastian Thrun, and
Gary Bradski

Stanford University, Intel Corporation

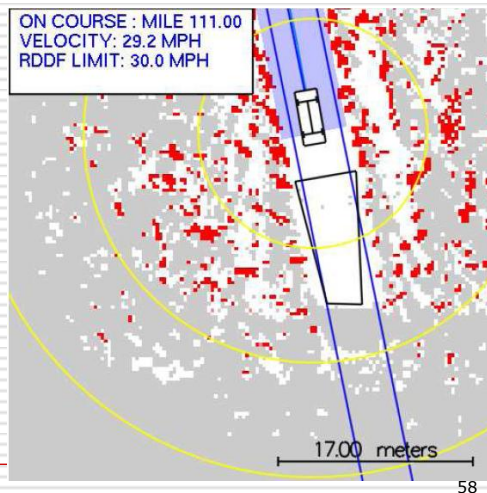
Goal: Detect drivable surface for aiding speed calculations



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Extract "training" area using laser data

- Project onto camera image
- Assume that area contains only drivable surface
- Remove sky and shadows
- Range: ~22m



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Learn visual model of nearby road

- Approximate using mixture of k Gaussians in RGB space
- Additional Gaussians describing training history

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Score visual field by road model

- Use distance from each pixel to nearest Gaussian to assign a "roadness" score.



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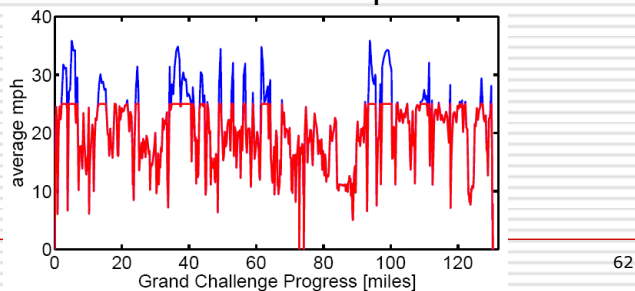
Select identified patches

- ❑ Threshold image points further away than 3σ to get a binary drivability image.
- ❑ Run several filters to remove small non-drivable areas (rocks, leaves) while preserving bigger obstacles.



Usage

- ❑ Used as pre-warning system for capping speed (if can't see clear road for 40m).
- ❑ Ran at 12fps on single processor on 320 x 240 images.
- ❑ Extended road detection to up to 70m.



Pretty video...
