Environmental Classification for Indoor/Outdoor Mapping with UGVs

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Outline

- Motivation
- Adaptive Perception System
- Experimental Results
- Conclusions
- Future Work
- Questions

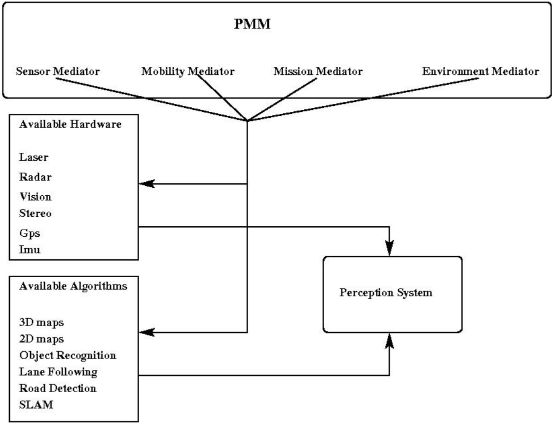
Motivation
Current Perception Systems

- Traditionally UGVs and algorithms focus on one specific environment (Ex. Indoor/Outdoor, static/dynamic)
- Need to adapt to changing environment seamlessly
- Adapt/change perception and navigation techniques
- Increase operational range of UGV
- More complex missions
- Improved robustness and less failure

Motivation
Perceptual Needs

Perceptual Needs can be determined by 4 factors:

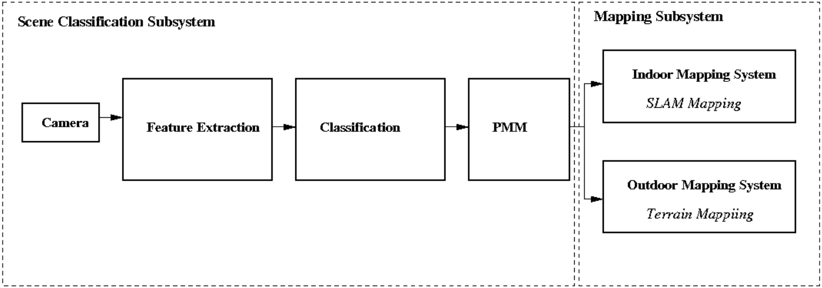
- Mission
- Mobility
- Sensors
- **Environment**



Adaptive Perception System

- Indoor/Outdoor Classification for an adaptive perception system
- Adapt/change the UGVs perception system based on the classification results
- Globally consistent mapping of indoor/outdoor environments
- Starting point for an Adaptive Perception Architecture

Adaptive Perception System



Adaptive Perception System
Image Features

- Measurable statistic of an image or image regions
- Want features that are detectable, relevant and invariant to changes in rotation, scale and illumination
- Data reduction
- Use sub-images to retain spatial information
- Used as input to a supervised learning technique

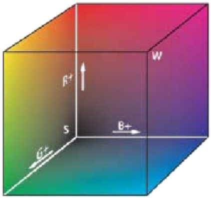
- HSV, RGB, and LUV histograms
- Orientation Histogram
- Curvature Histogram
- HSV, LUV colour moments

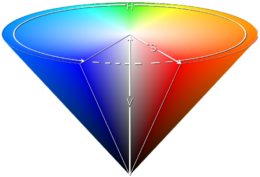
Adaptive Perception System
Colour spaces

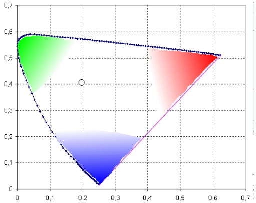
RGB colour space

HSV colour space

LUV colourspace



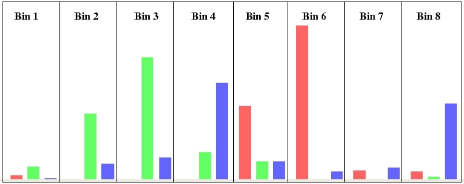




- RGB - Red, Green, Blue
- HSV - Hue Saturation, Value
- LUV - Luminance and Chrominance

Adaptive Perception System
Colour histograms

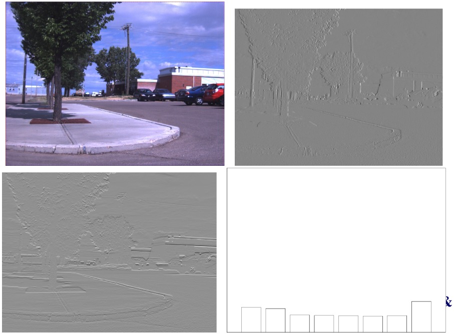
- Partition colour space into discrete bins
- Sum the instances of each bin
- Normalize to reflect percentage of pixels



Adaptive Perception System

Orientation Histogram

- Pass gray image through vertical and horizontal edge detectors
- Determine the orientation of the gradient at each pixel
- Distretize the orientation space
- Sum instances of each orientation and normalize



Adaptive Perception System
Curvature histograms

Curvature Histogram

- Calculate the magnitude of curvature rather than the orientation of local structures
- Distretize the curvature magnitude
- Sum instances of each magnitudes and normalize

$$M = \begin{pmatrix} \frac{dI}{dx}^2 & \frac{dI}{dx}\frac{dI}{dy} \\ \frac{dI}{dx}\frac{dI}{dy} & \frac{dI}{dy}^2 \end{pmatrix} \quad (1)$$

Adaptive Perception System
Colour moments

- 1^{st} and 2^{nd} order colour moments (mean and standard deviation)
- Calculated for each channel of the colour space

$$E_i = \sum_{j=1}^{N} \frac{p_{ij}}{N} \tag{2}$$

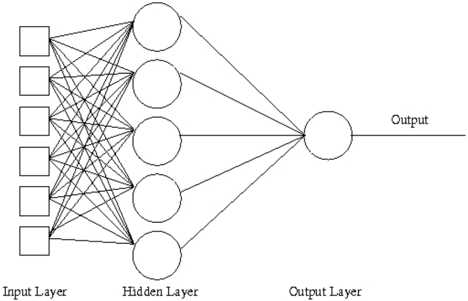
$$\sigma_i = \sqrt{\frac{\sum_{j=1}^{N}(p_j - E_i)^2}{N}} \tag{3}$$

Adaptive Perception System
Supervised Learning Techniques

- Trained using input features/target classification pairs $< x_i, t_i >$
- Train classification function by reducing error between target and output
- Feed Forward Artificial Neural Networks and Support Vector Machines examined here

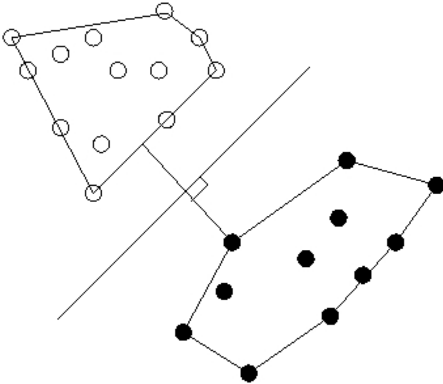
Adaptive Perception System
Neural Networks

- Input layer - Image feature vector
- 40 neurons in the hidden layer
- Sigmoid activation function
- 1 output neuron
- backpropagation algorithm



Adaptive Perception System
Support Vector Machines

- Finds *Optimal* hyperplane between dataset (Maximum margin)
- Input layer - Image feature vector
- Same inputs and targets as with NN
- Kernal mapping (RBF)



Adaptive Perception System Perception Mediation Module

- Constantly monitors classification output
- Monitors current system to ensure all processes are running
- Uses indoor/outdoor counters to disregard erroneous classifications
- When environment transition occurs:
    - Kills previous perception system
    - Launches new perception system

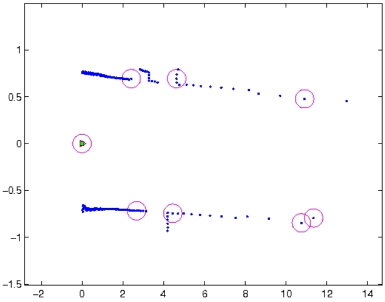
Adaptive Perception System
EKF SLAM - Algorithm

$$X_k = \begin{pmatrix} V_k \\ M_k \end{pmatrix} \quad , \quad P_k = \begin{pmatrix} P_v & P_{vm} \\ P_{vm}^T & P_m \end{pmatrix} \qquad (4)$$

- **Prediction** - State and covariance calculated from previous state and covariance, and the control u_k.
- **Data Association** - Find matches between the current landmarks M_k and observed features z_k.
- **Measurement Update** - Calculate the Kalman gain for each observed landmark and update the state and covariance.
- **Augmentation** - Integrate new landmarks into the state and covariance.

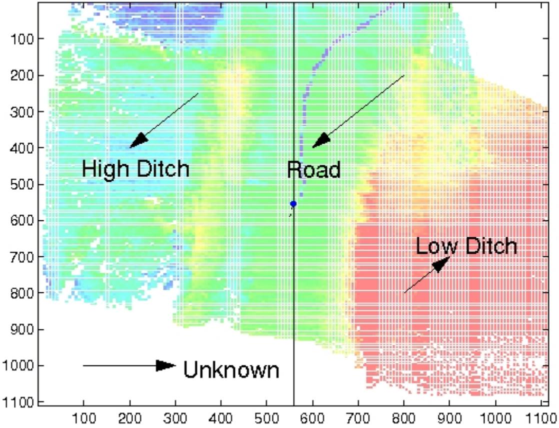
Adaptive Perception System EKF SLAM - Laser Feature Extraction

- Extract features from Raw laser data
- Incremental algorithm (line tracking)
  - Fit a line to a set of points
  - Compute the residual
  - If below error threshold add another point and repeat
  - If above the last point added is a feature



Adaptive Perception System

Terrain Mapping



Experimental Results
Hardware and 3^{rd} Party Software

Hardware	3rd Party Software
Pioneer 3AT	Matlab
Flea Camera	EpsiloNN
Bumblebee Stereovision	libSVM
SOKKIA GPS	Miro/LibVideoFilters
DPGS Radio	Gazebo Simulator
Microstrain IMU	Tim Bailey SLAM Simulations
SICK Laser	

Experimental Results
Scene Classification

- Training/validation data gathered from 3 different environments
- Used 3 training scenarios (different % of training/validation images)
- Created feature vectors and analyzed results offline
- All image feature and learnig method combination
- Whole image features and sub-image features

Experimental Results
Scene Classification

Whole Image Features						
Feat.	**Percentage Correct**					
	Scenario 1		Scenario 2		Scenario 3	
	ANN	SVM	ANN	SVM	ANN	SVM
RH	95.35	96.51	96.62	88.24	95.12	95.55
HH	**98.84**	**99.84**	**99.68**	**99.68**	**96.56**	**97.42**
LH	98.45	97.87	99.03	97.58	96.27	96.84
OH	65.31	87.02	65.38	86.63	56.81	83.21
CH	48.06	65.31	47.99	66.83	48.06	61.26
HM	48.06	98.64	47.99	98.39	48.49	97.13
LM	48.06	73.64	47.99	77.78	48.06	78.19

- Excellent results with colour histogram features
- Orientation and Curvature Histograms perform poorly
- Colour moments inconsistent
- HSV performs best regardless of learning technique

Experimental Results
Scene Classification

Sub-Image Features						
Feat.	**Percentage Correct**					
	Scenario 1		Scenario 2		Scenario 3	
	ANN	SVM	ANN	SVM	ANN	SVM
RH	95.16	95.93	95.97	96.46	91.10	89.67
HH	**98.84**	**99.03**	**99.84**	**99.68**	**96.41**	**97.42**
LH	98.64	98.84	97.91	98.87	96.13	96.84
OH	86.63	90.12	81.64	88.24	81.92	85.94
CH	76.36	82.95	73.91	81.16	72.88	76.47
HM	48.84	90.68	53.46	89.05	57.53	86.66
LM	49.22	94.96	48.79	98.23	48.78	92.25

- HSV performs the best regardless of learning technique
- Increase in classification accuracy (8% ANN)
- Virtually no difference for Colour Histograms
- Orient and Curve histograms saw largest benefit

Experimental Results
Scene Classification

Generalization - Whole Image						
Feat.	**Percentage Correct**					
	Scenario 1		Scenario 2		Scenario 3	
	ANN	SVM	ANN	SVM	ANN	SVM
RH	70.55	70.06	82.04	63.75	72.33	67.31
HH	70.39	75.40	71.20	**73.14**	74.60	74.11
LH	**73.46**	**76.86**	**76.05**	63.43	**76.38**	**75.89**
OH	57.93	62.95	63.27	64.89	59.39	66.99
CH	42.40	57.77	42.40	64.72	42.40	62.14
HM	42.40	66.18	42.40	69.42	49.19	68.45
LM	42.40	66.99	42.40	64.89	42.40	74.43

- Sharp decrease in performance
- LUV performs slightly better than HSV
- Doesn't generalize well
- Several classifiers below 50% (worse than guessing?)

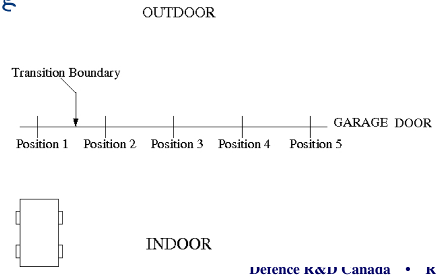
Experimental Results
Scene Classification

Generalization - Sub Image						
Feat.	**Percentage Correct**					
	Scenario 1		Scenario 2		Scenario 3	
	ANN	SVM	ANN	SVM	ANN	SVM
RGB Hist	77.02	73.30	71.20	67.80	68.61	65.70
HSV Hist	**80.74**	76.38	**82.04**	80.10	**78.64**	76.54
LUV Hist	77.35	**77.83**	80.91	**81.23**	77.18	**77.99**
Orient Hist	69.74	68.12	65.05	61.65	67.48	61.81
Curve Hist	63.12	68.28	55.66	66.18	64.89	70.23
HSV Moments	50.00	57.61	57.12	57.61	68.12	57.61
LUV Moments	42.39	77.35	43.20	57.61	44.01	57.61

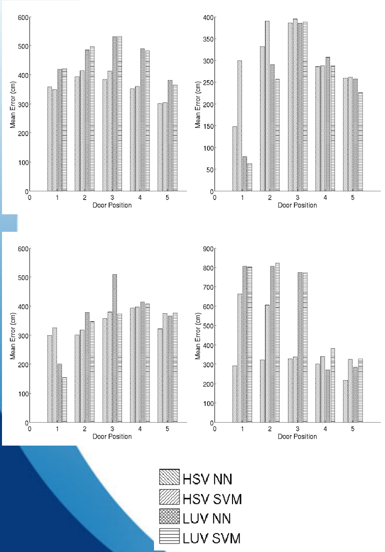
- HSV and LUV histogram learners most accurate
- Roughly 5.5% increase in accuracy across HSV/LUV hist tests
- HSV ANN is the best performer
- Further tests only HSV/LUV with sub-imaging

Experimental Results
Transition Analysis

- Consider the HSV/LUV histograms with sub-imaging
- Maneuver pioneer towards a door opening at intervals
- Error = distance between robot bumper and door opening



Experimental Results
Transition Analysis

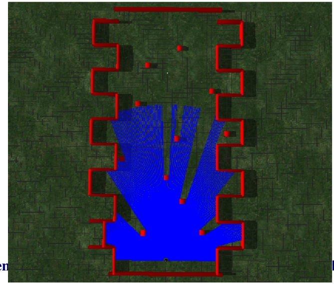


Input Feature	NN		SVM	
	μ	σ	μ	σ
HSV Hist	316.47	59.47	376.96	95.38
LUV Hist	421.64	189.71	414.23	194.6

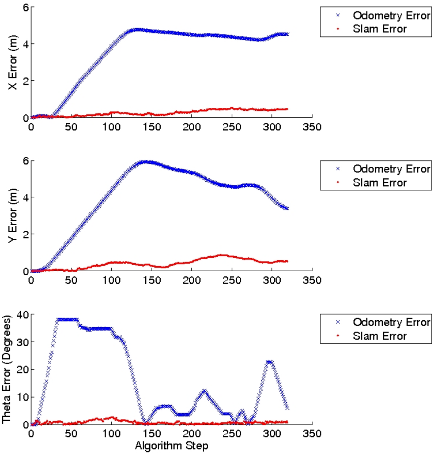
- Larger error near middle
- HSV based classifiers outperform LUV
- HSV with NN learning
- LUV less robust to lighting (large σ)

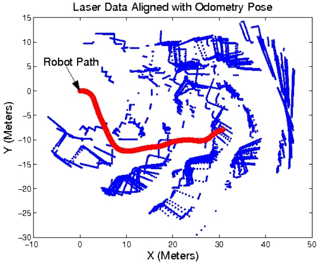
Experimental Results
SLAM Simulation

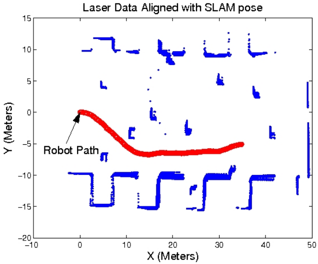
- Use Gazebo 3D Robotics Simulator to collect data
- Evaluate/Tune SLAM algorithm with Simulated data
- Advantages:
  - Can compare to ground truth
  - No hardware problems
  - Use same Code/hardware to interface to Gazebo or actual robot (Miro, Joystick)
  - Can control the environment



Experimental Results
SLAM Simulation







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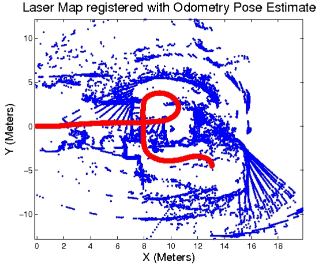
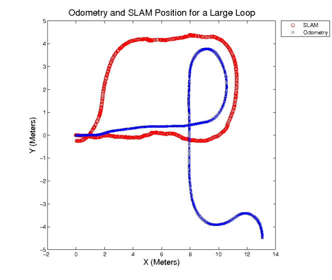
Experimental Results
SLAM Loop

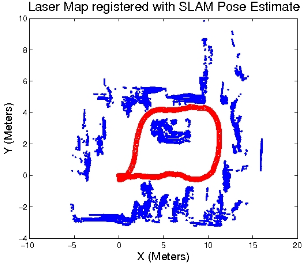
- SLAM with real hardware
- No ground truth data available
- Test accuracy around large loop
- Express error as % of distance travelled

Experimental Results
SLAM Loop

- Two separate runs
- Error of less than 1% of the distance travelled
- Move slowly (lots of overlap)
- Problem areas required parameter tuning

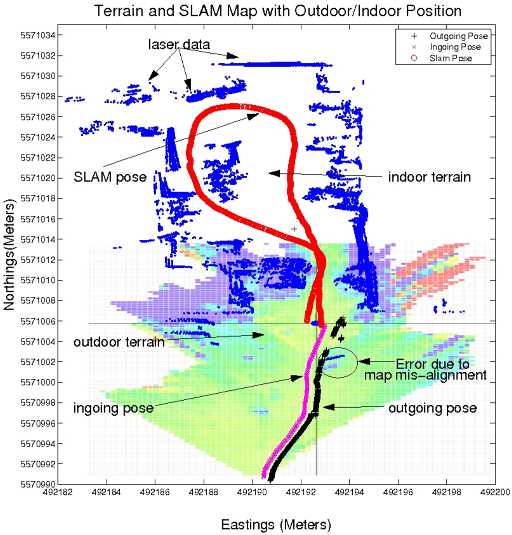






Experimental Results
Full System

- Full indoor/outdoor map in global reference
- Indoor mapping in SLAM reference
- Homogenous transform to put in global reference
- Some inconsistencies
- GPS flucuation



Conclusions

- Framework for assessing perceptual needs of a UGV
- Qalitative assessment of different image features and leaerning techniques
- Novel approach to indoor/outdoor mapping (PMM)
- EKF SLAM system accurate to within 1% of the distance travelled
- Shown that Colour histograms are an effective image feature for indoor/outdoor classification
- HSV features with ANN learning provided the best classification accuracy while being robust to lighting conditions
- Sub-imaging improves classification and generalization to new environments

Future Work

- Improve robustness/accuracy of indoor/outdoor mapping system
  - FastSLAM
  - Submap and/or hybrid mapping techniques
  - VSLAM for outdoor (no reliance on GPS)
- Further environmental classification (urban/rural, forest/open etc.)
- Improve classification accuracy
  - Boosting techniques (AdaBoost)
  - Non-linear data reduction (Isomap, PCA, ICA, etc.)
  - Alternative classification techniques (RVM)
  - multi-camera or omnidirectional camera system

Questions