Online Learning for Offroad Robots:

Using Spatial Label Propagation to Learn Long-Range Traversability

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Problem Definition

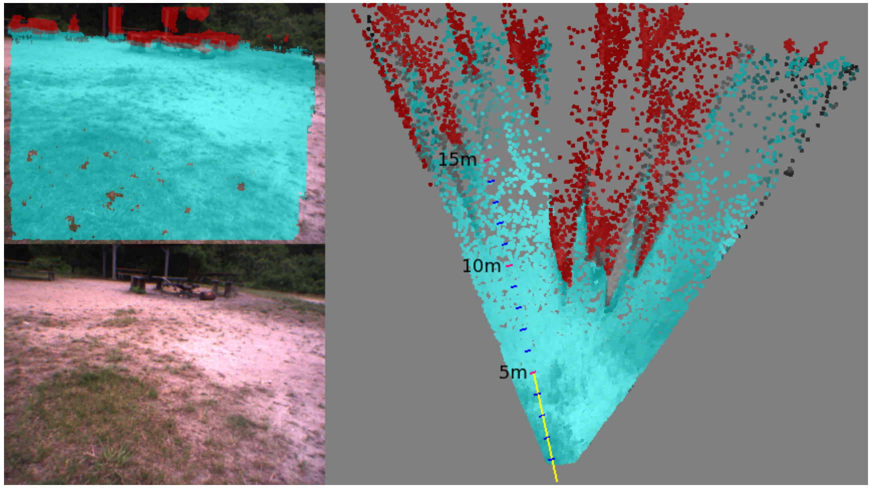
- Vision-based Navigation for Mobile Robots
  - Structured indoor environments
  - Unstructured indoor environments
  - Structured outdoor environments (road-following)
  - **Unstructured outdoor environments**
    - goal vs. non-goal driven

Problem Definition

- Vision-based Navigation for Mobile Robots
  - **Unstructured outdoor environments**
  - Primary tasks (for goal-driven systems):
    - Obstacle avoidance
    - Landmark detection
    - Path planning
    - Position estimation
    - Map building

Motivation: stereo shortcomings

- Vision-based navigation often done using **stereo**
  - Find **disparities** between 2 calibrated camera images
  - Ground/obstacle points identified using estimated ground plane



  - Stereo maps are short-range, noisy, and prone to error (tall grass)
  - Navigating in fog

Motivation: Beyond Stereo

- Beyond stereo: Long-range obstacle detection
  - Obstacles, cul-de-sacs, dead ends
  - promising paths
  - manmade structures
  - collapsible vs. non-collapsible vegetation
- Robustness
  - adaptation to new terrain
  - memory of old terrain

Previous Work

- **Supervised Learning** applied to Autonomous Navigation
  - Learning steering angles directly from images:
    - ALVINN [Pomerlau, Robot Learning, 1993]; MANIAC [Jochem et al., IROS, 1995]
    - DAVE [LeCun et al., NIPS, 2005]
    - [Gaussier et al., IROS 1997], [Jones et al., IROS 1997]
  - Learning obstacles from images:
    - NEURO-NAV [Meng and Kak, ICRA 1993]
    - [Manduchi et al., Autonomous Robot 2003]
    - [Huertas et al., Workshop of Applications of Computer Vision 2005]
    - Demo III [Hong et al., Aeroscience Conference 2002]
    - [Hong et al., ICRA 2002]
    - [Rasmussen, ICRA 2002]

Previous Work

- **Self-Supervised Learning** applied to Autonomous Navigation
  - *Near-to-Far* Learning: A reliable (but limited scope) module provides labels to train another module (with wider scope).
    - LADAR module ---> satellite image pixels (traversability)

      [Sofman et al. Improving robot navigation through self-supervised online learning. RSS 2006.]
    - Wheel data ---> LADAR features (terrain roughness)

      [Stavens, Thrun. A self-supervised terrain roughness estimator for offroad autonomous driving. UAI 2006.]
    - Wheel data ---> LADAR features (load-bearing surface)

      [Wellington, Stentz. Online adaptive rough-terrain navigation in vegetation. ICRA 2004.]
    - Vehicle location ---> color camera patches (road detection)

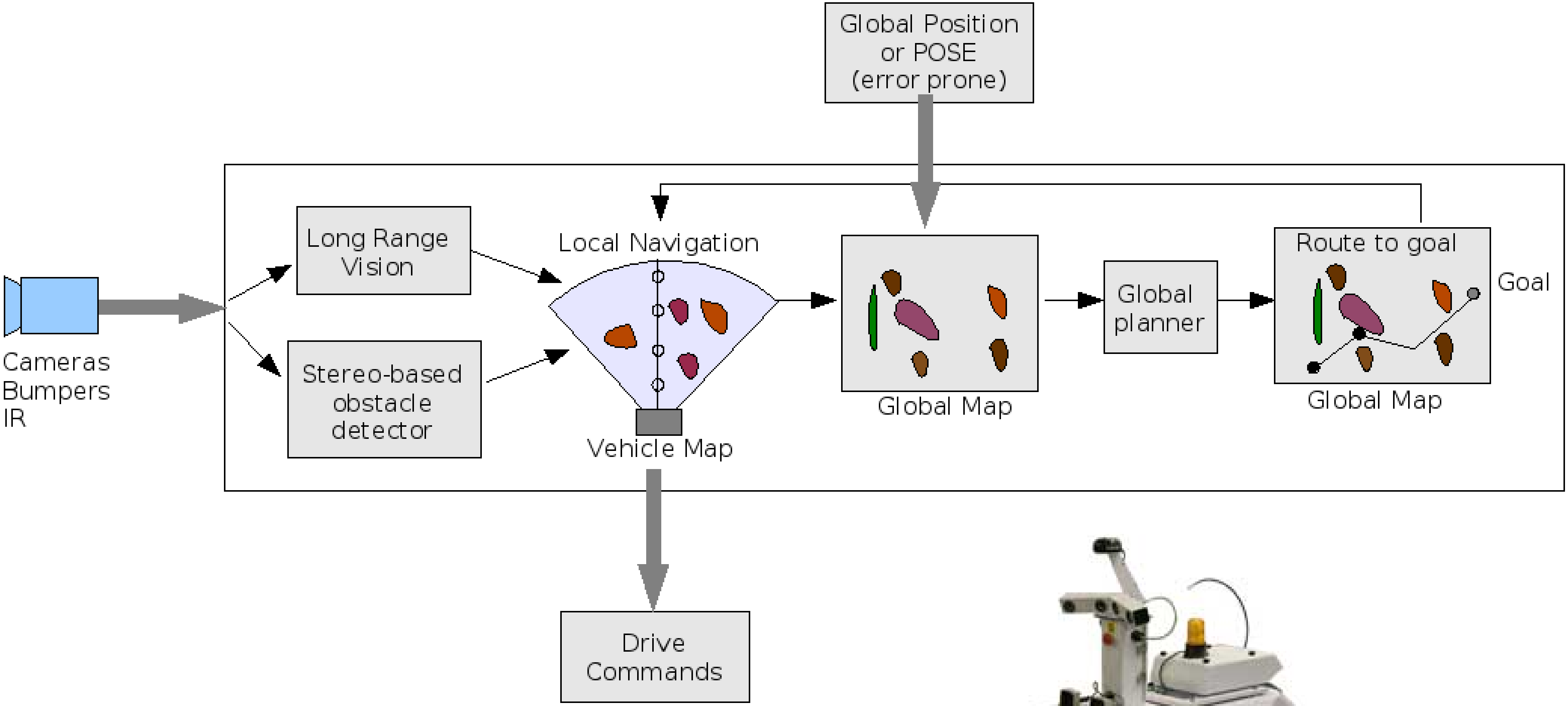
      [Dahlkamp et al. Self-supervised monocular road detection in desert terrain. RSS, June 2006.]
    - Bumper hits, wheel current --> color camera features (traversability)

      [Kim et al. Traversibility classification using unsupervised on-line visual learning for outdoor robot navigation. ICRA 2006]

LAGR Robotic Platform

- **LAGR** (Learning Applied to Ground Robots)
  - DARPA program 2005-2008
  - 8 competing research labs develop navigation software for single platform
  - Periodic testing in unfamiliar terrain
  - CMU/NREC designed platform and baseline software
  - **Platform**:
    - 4 color cameras (2 stereo pairs, 640x480)
    - GPS receiver
    - 2 front bumper switches
    - Onboard IMU (inertial measurement unit)
    - 4 onboard 1.2Ghz computers

LAGR Robotic Platform



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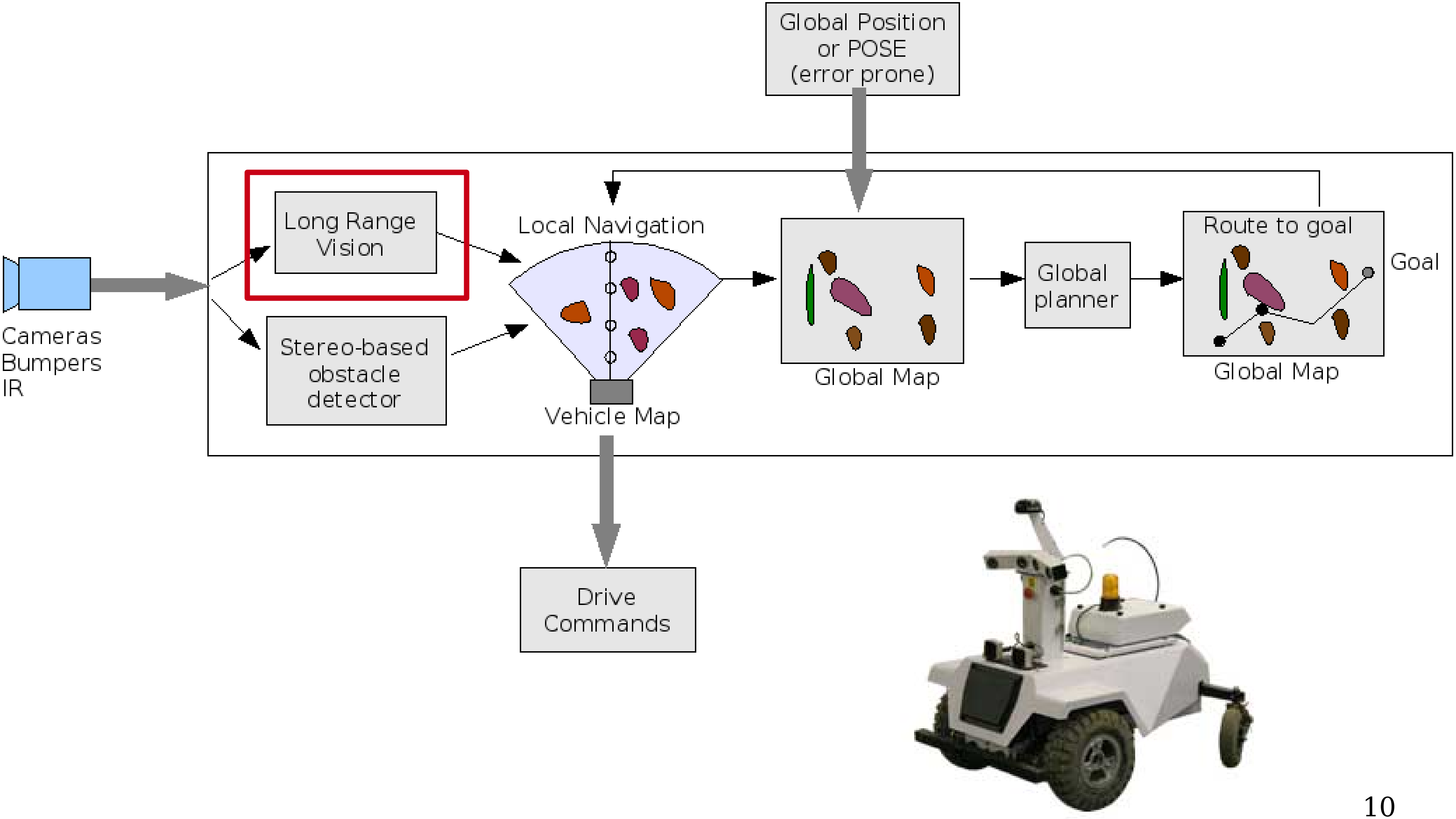

Learning Framework

- Paradigm: Near-to-Far Self-Supervised Learning
  - **Inputs**: large windows from image
  - **Labels**: Stereo module
  - **Classifier**: convolutional neural network (feature extraction)
    + online logistic regression

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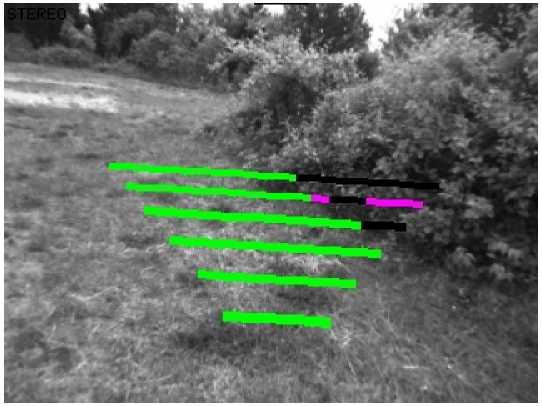

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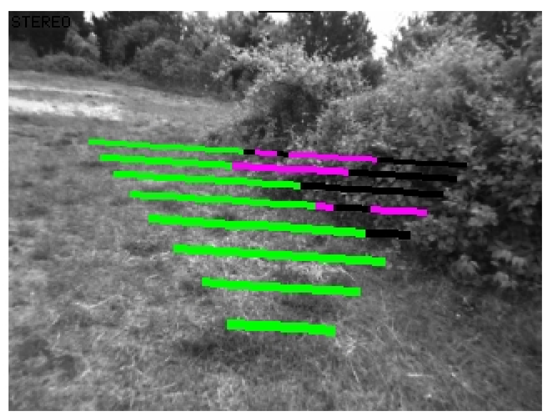

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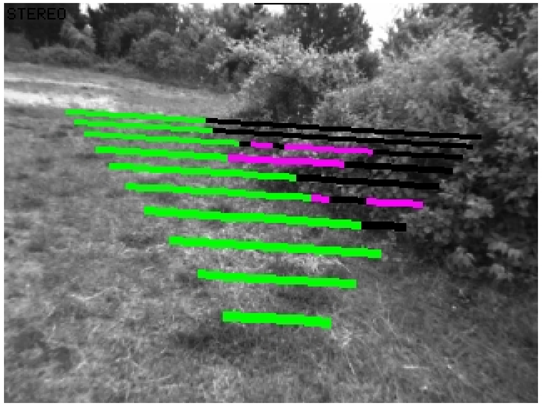

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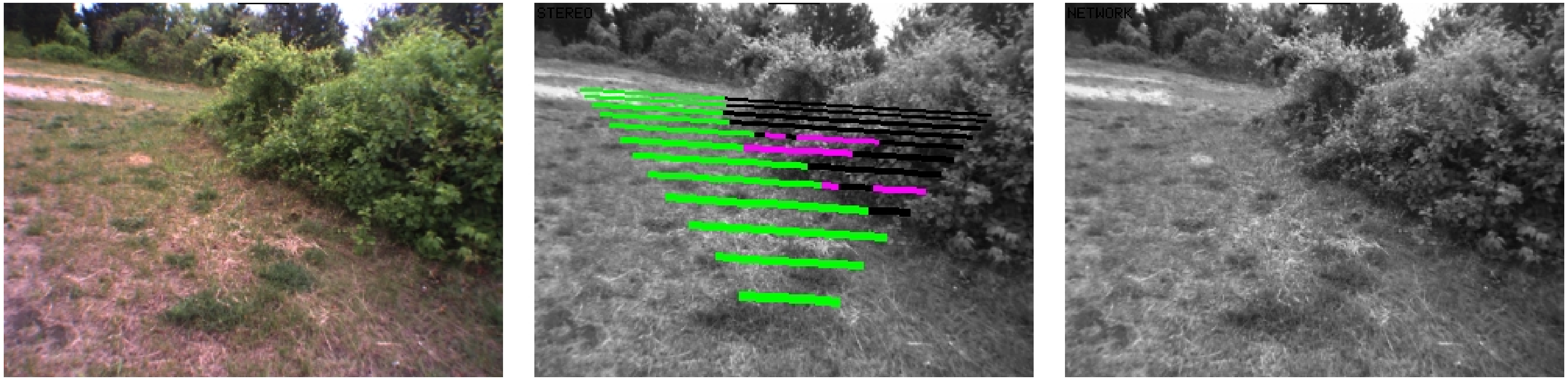

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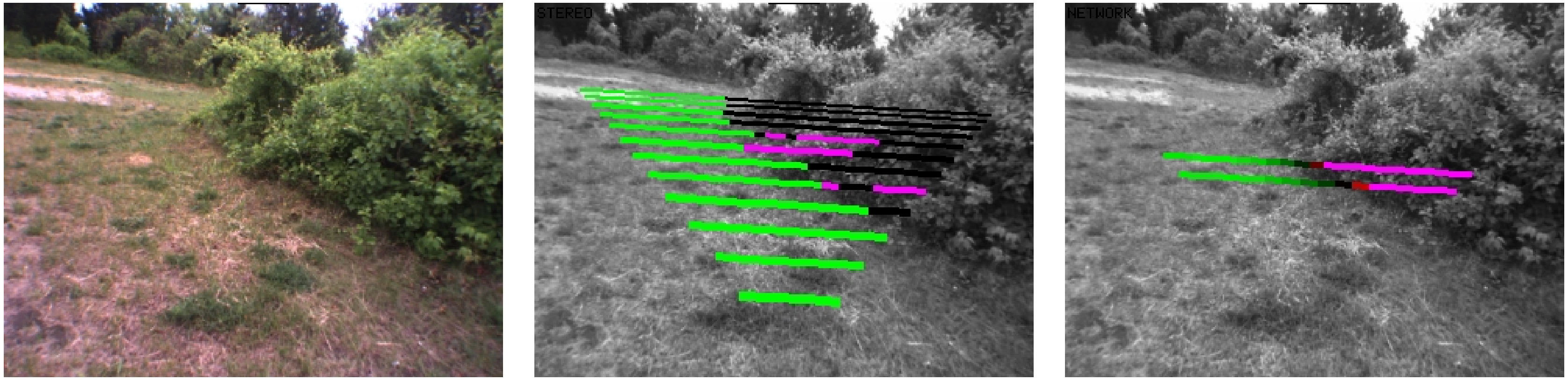

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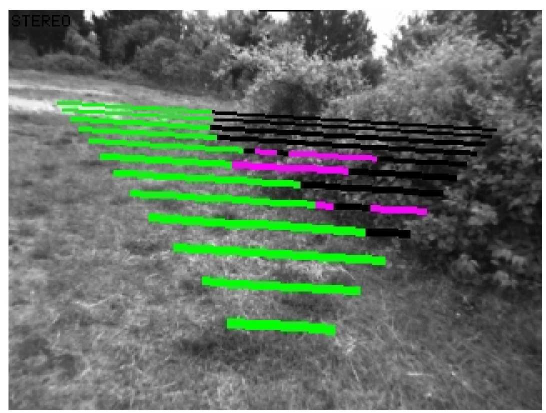

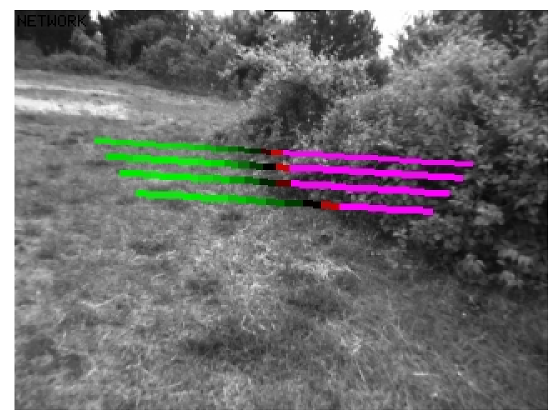

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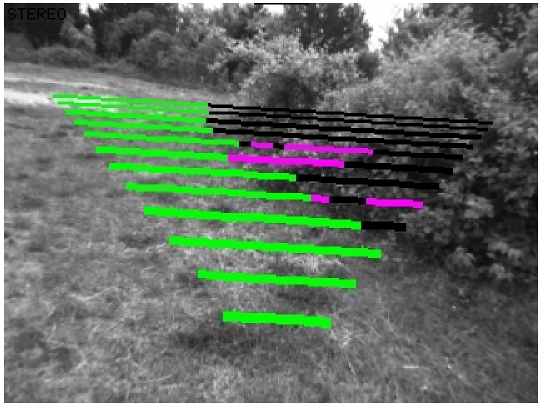

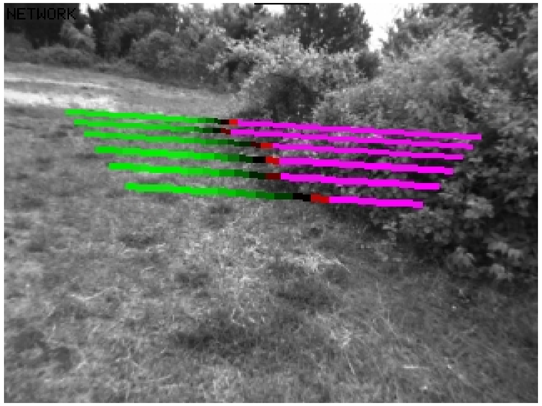

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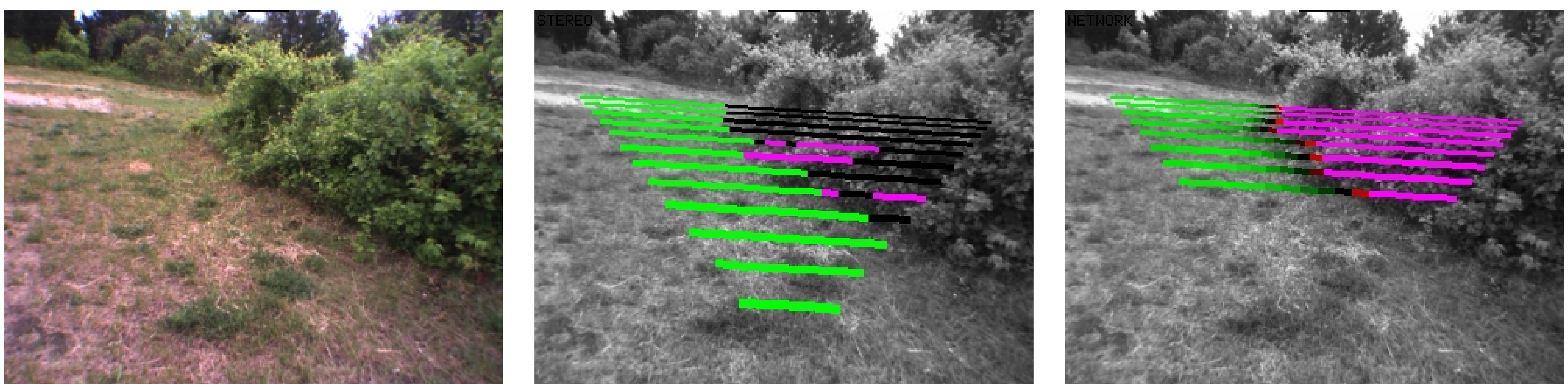

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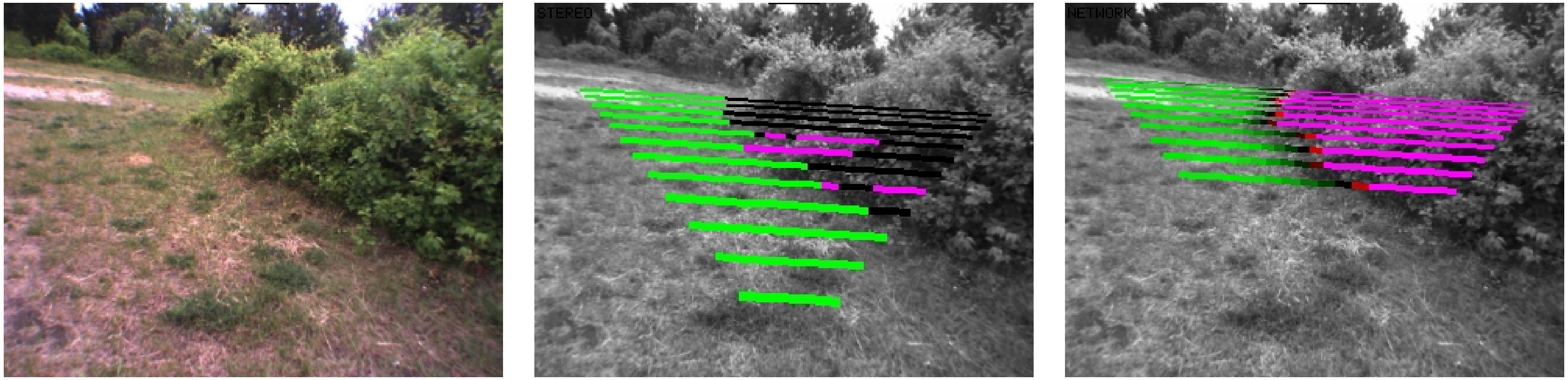

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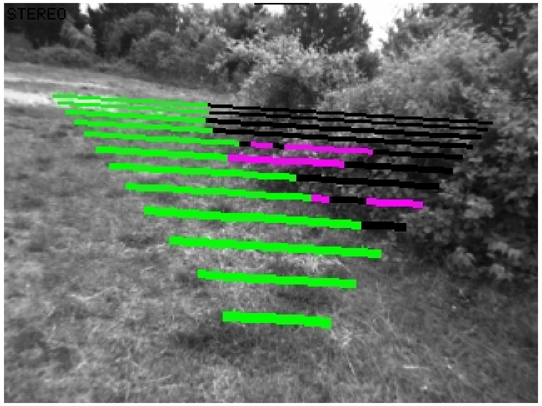

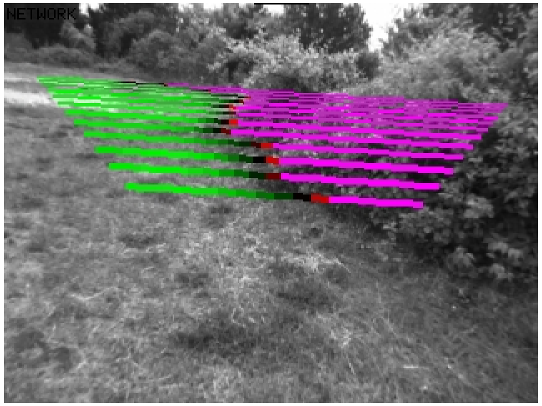

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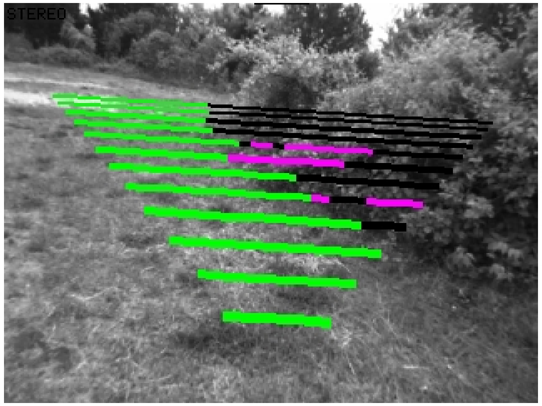

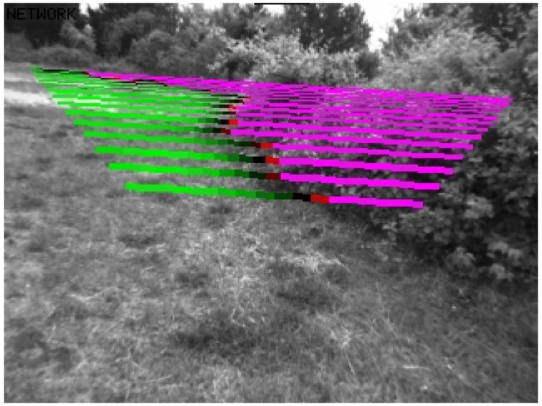

Control Loop Overview

I. **Pre-Processing**

II. Labeling and Feature Extraction

III. Label Propagation

IV. Online Training and Classification

Control Loop: Preprocessing

I. Pre-Processing

1) Image rectification and stereo algorithm -> **image + point cloud**
2) Ground plane estimation -> image + point cloud + plane equation
3) Convert to YUV, normalization -> YUV image + point cloud + plane eq.
4) Horizon leveling and distance/scale normalization -> image pyramid

Control Loop: Preprocessing

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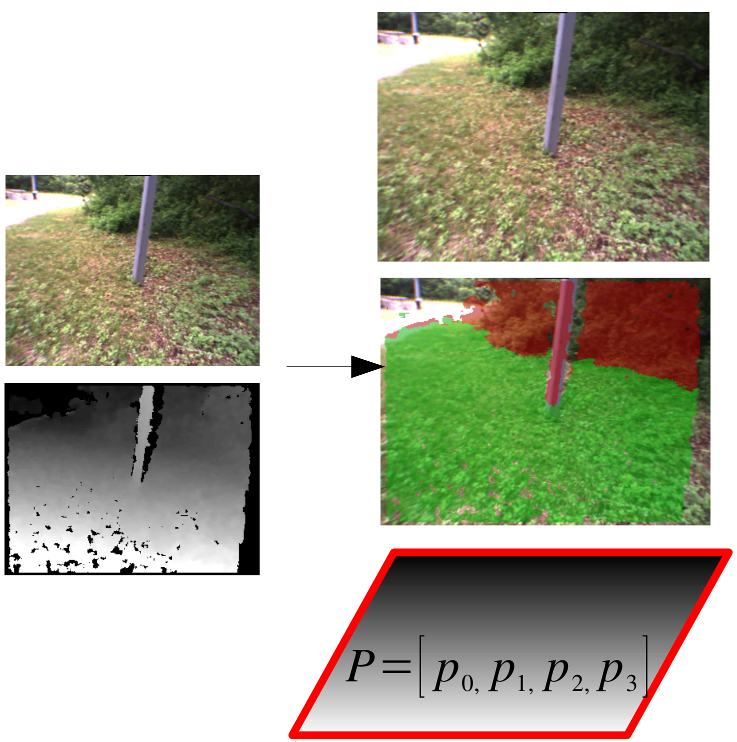

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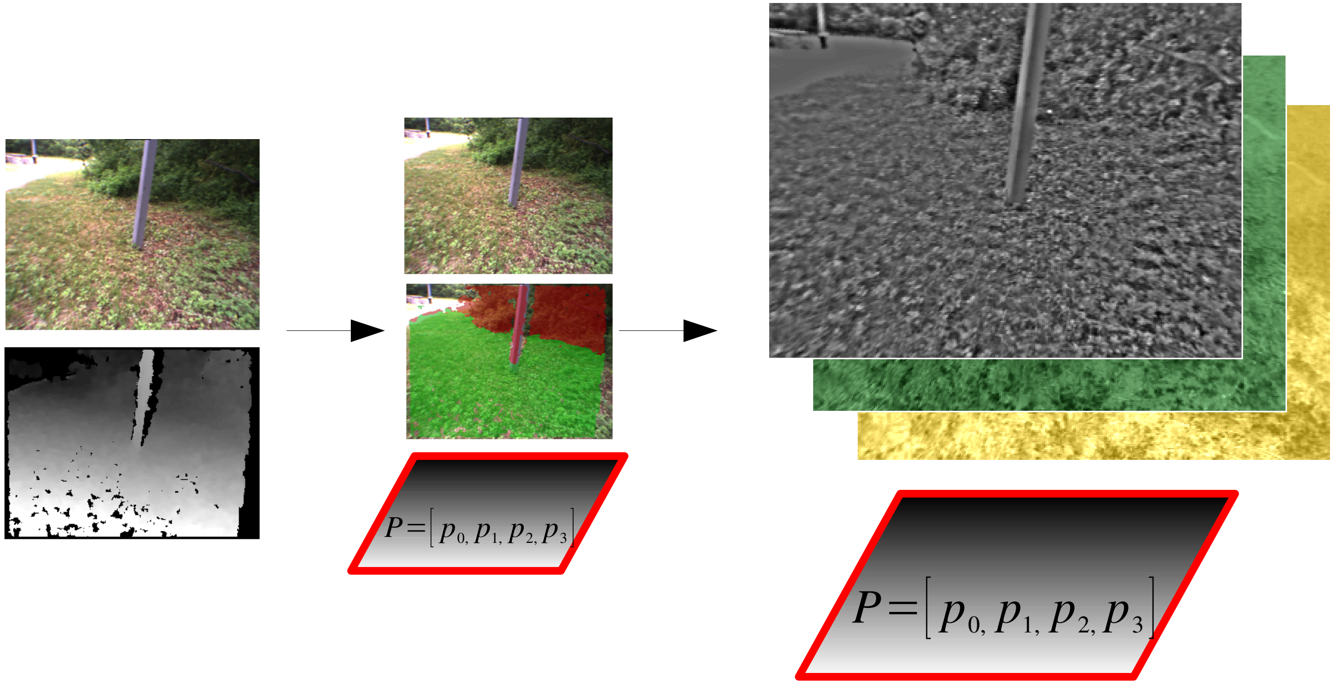

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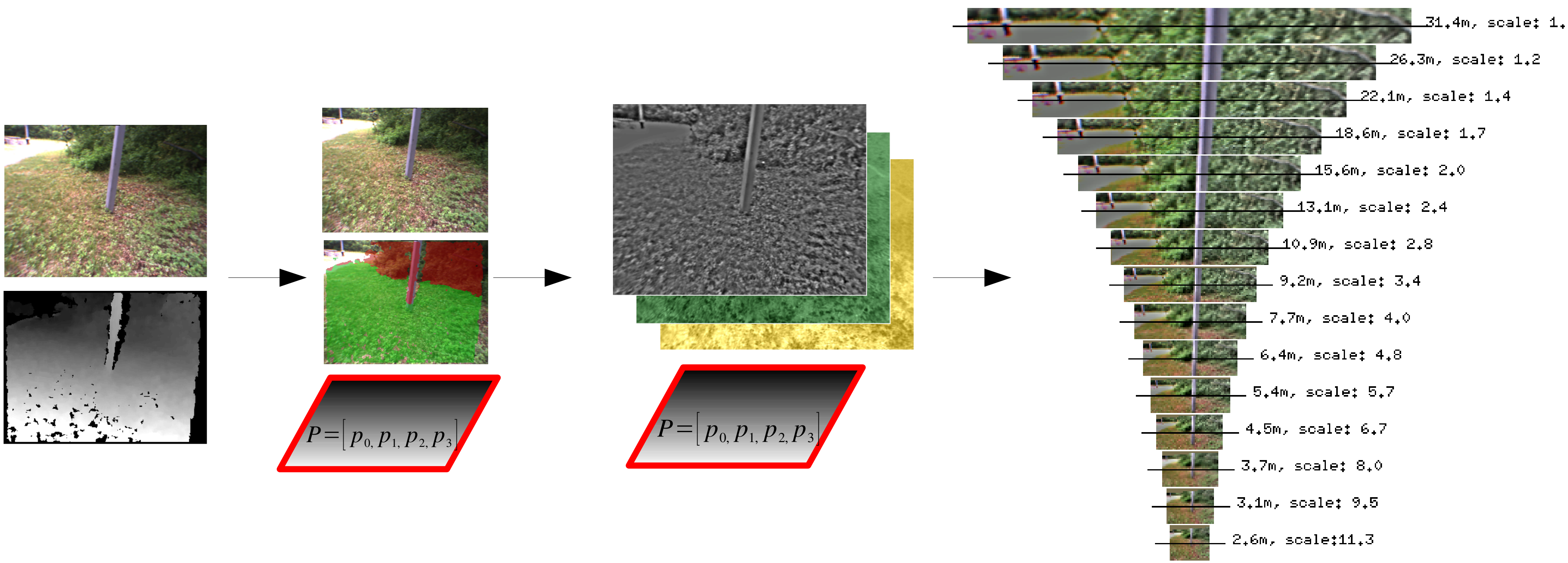
4) Horizon leveling, distance/scale normalization -> **image pyramid**



Preprocessing

- Distance-normalized image pyramid
  - Better learning with large windows rather than simple patches-
    - context, transitions, feet
  - But, aspect varies severely, makes generalization from near to far impossible
  - Solution: normalize so that height of an object is independent of distance from camera.

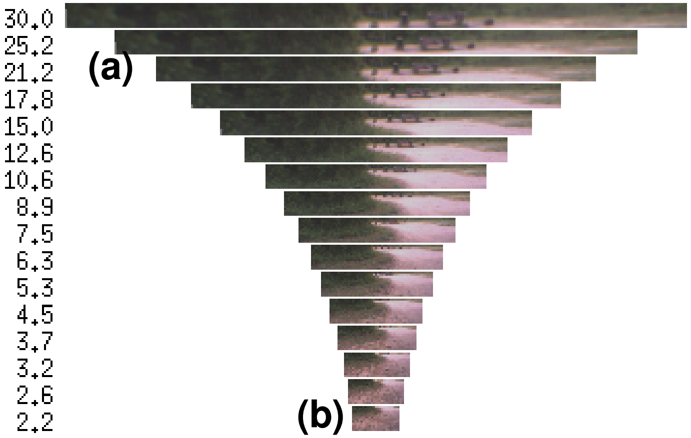
extracted windows distance-normalized

Preprocessing

- Distance-normalized image pyramid

(a). sub-image extracted from far range. (21.2 m from robot).

(b). sub-image extracted at close range. (2.2 m from robot).



(c). the pyramid, with rows (a) and (b) corresponding to sub-images at left.

- 20 bands from 1 to 35 meters
- Uniform height (16 pixels), variable width

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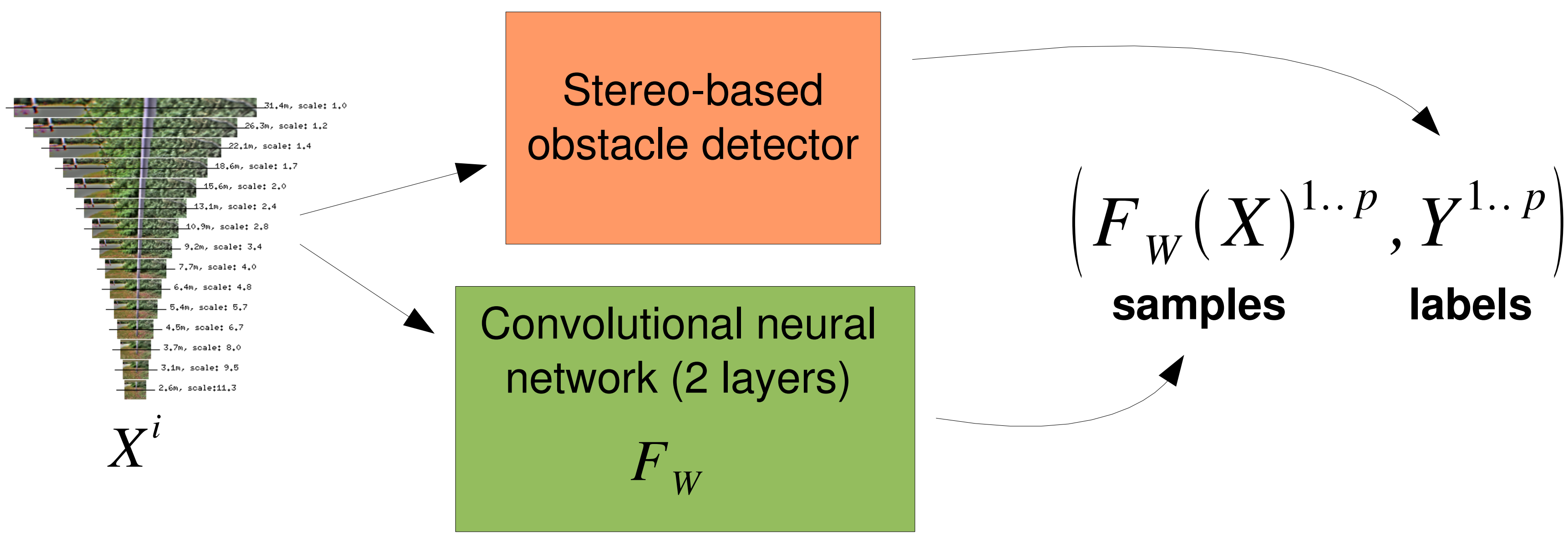
Control Loop: Training Set

II. Labeling and Feature Extraction

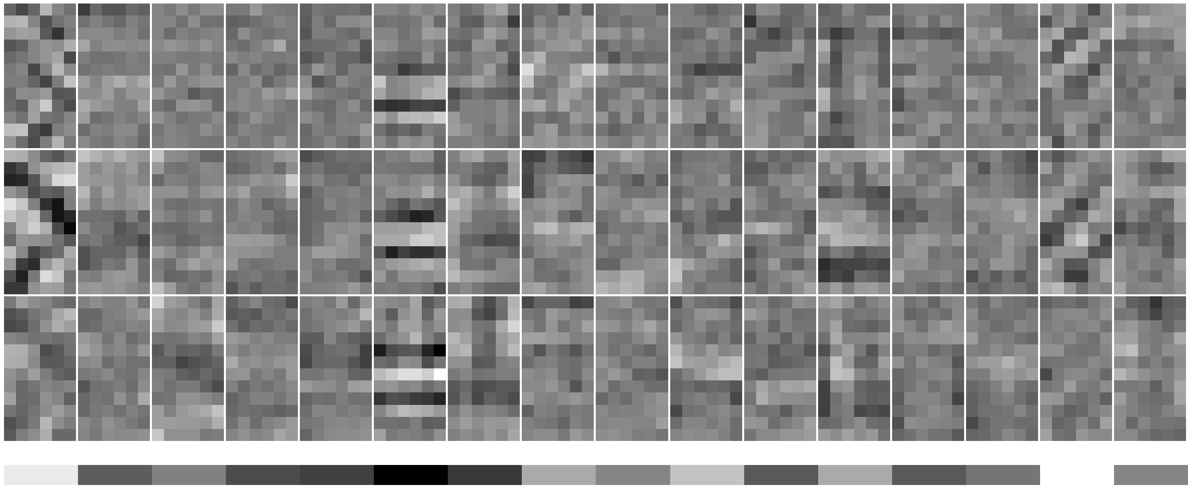
1) Histogram of stereo point cloud; heuristics to determine cost.
   -> training labels

2) Feature extraction using convolutional neural network
   -> pyramid of feature vectors



Feature Extraction

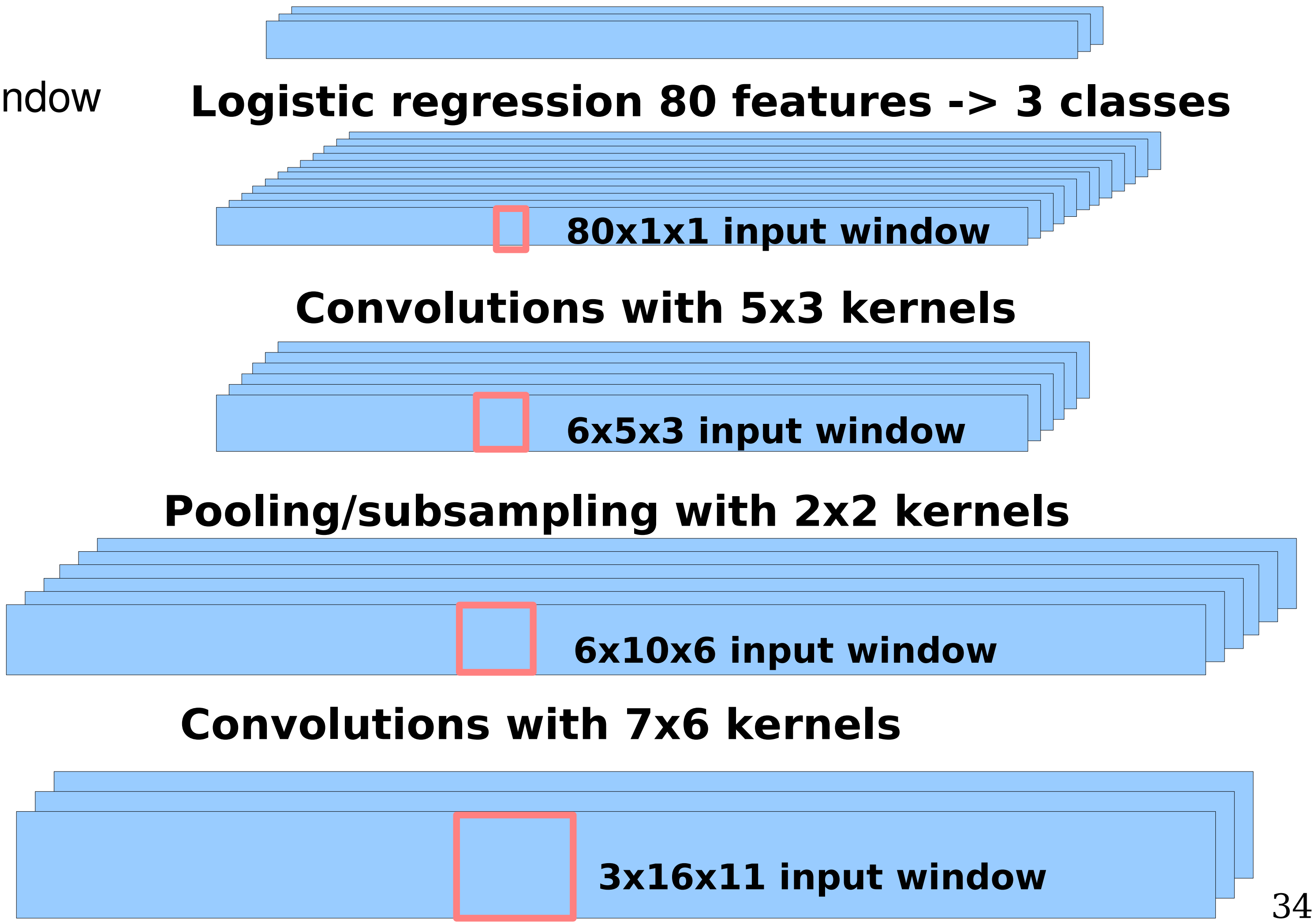
- Convolutional Neural Network:
  - Output of convolutional network: feature vector (120 components)
  - Trained offline using 150 diverse logfiles (1.2 million samples)
  - 48 7x6 filters (first layer), 5x3 filters (second layer), 80 outputs
  - Low-level features are pooled
  - Learns highly discriminative features
  - Naturally shift and scale invariant



Feature Extraction

- Convolutional Neural Network:

80 features per
3x16x11 input window



YUV image band
16 pixels tall

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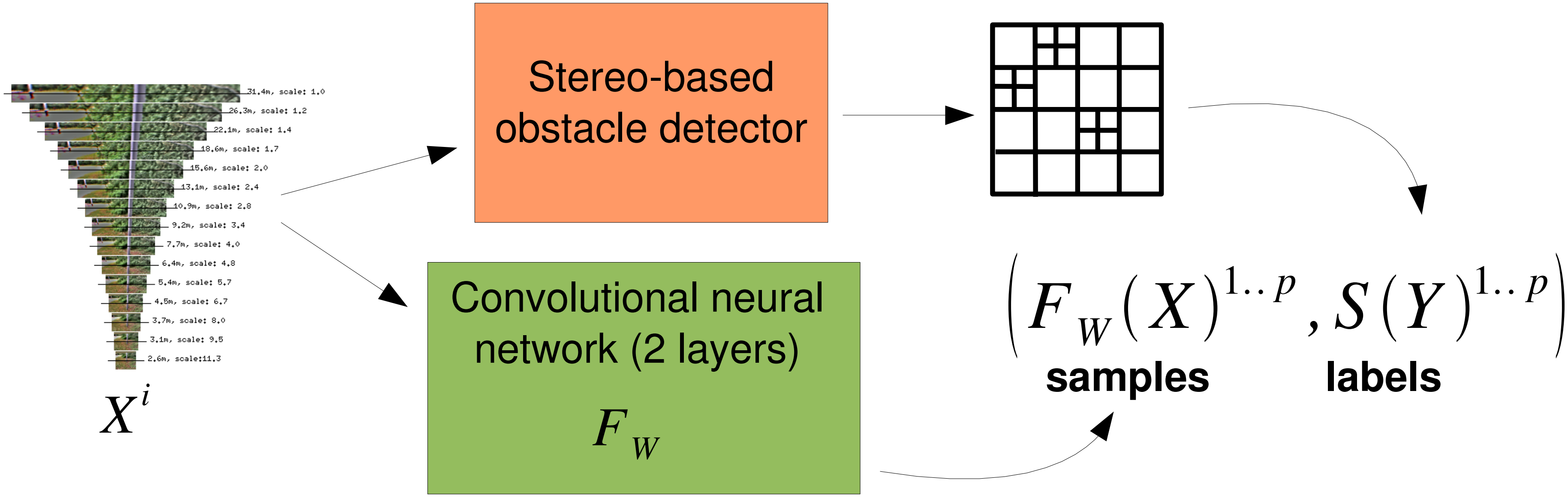
Control Loop: Training Set

III. Label Propagation

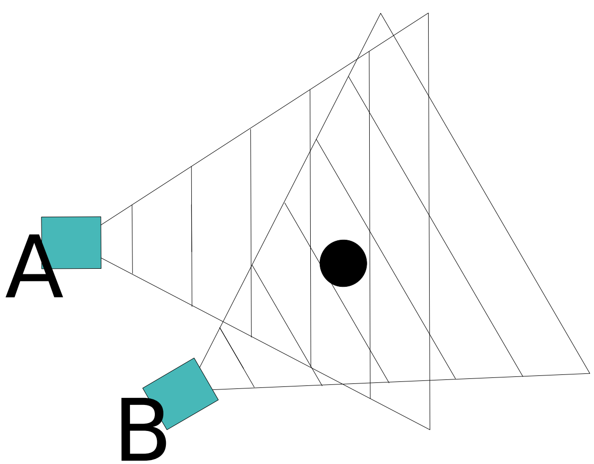
1) Insert current samples (feature vectors) into QuadTree
2) Query QuadTree for concurrent samples
3) Compute probabilistic labels

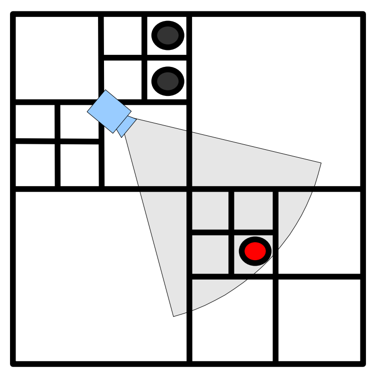
-> “soft” labeled pyramid



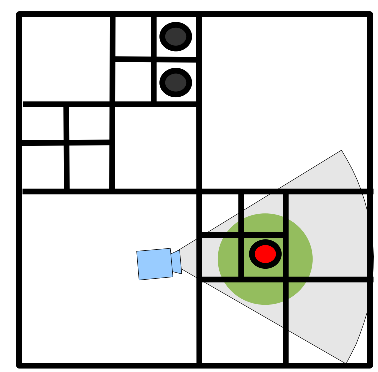
View-Invariant Training Samples

- Label Propagation with spatially indexed Quad-tree
  - *Time t*: $\mathbf{X}^{i}$ has coords (x,y) and label **?**
  - *Time t*: Add $\mathbf{X}^{i}$ to quad-tree at position (x,y)
  - *Time t+n*: Stereo gives label $\mathbf{Y}^{i}$ to coords (x,y)
  - *Time t+n*: Extract $\mathbf{X}^{i}$ and train with label $\mathbf{Y}^{i}$





Object is inserted
without a label at time A



Query extracts object at
time B and assigns a label

View-Invariant Training Samples

- Query at coords (x,y) yields samples $\mathbf{X}^i$ and (possibly) labels $\mathbf{Y}^i$:
  $\{(\mathbf{X}^1,\mathbf{Y}^1),(\mathbf{X}^2,\mathbf{Y}^2),\ldots(\mathbf{X}^m,\mathbf{Y}^m)\}$
- Compute probabilistic, ***soft*** label across $\mathbf{Y}$:

$$P_{ob}=\frac{|Y^i=ob|}{|Y^i=ob|+|Y^i=gr|} \qquad P_{gr}=\frac{|Y^i=gr|}{|Y^i=ob|+|Y^i=gr|}$$

- And propagate over all samples: $\{(\mathbf{X}^1,\mathbf{Y}^s),(\mathbf{X}^2,\mathbf{Y}^s),\ldots(\mathbf{X}^m,\mathbf{Y}^s)\}$

$\mathbf{Y}^1=?$ $\mathbf{Y}^2=-1$ $\mathbf{Y}^3=1$ $\mathbf{Y}^4=1$ $\mathbf{Y}^5=1$ $\mathbf{Y}^6=?$

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P=0.8 ***P=0.8*** ***P=0.8*** ***P=0.8*** ***P=0.8*** ***P=0.8***

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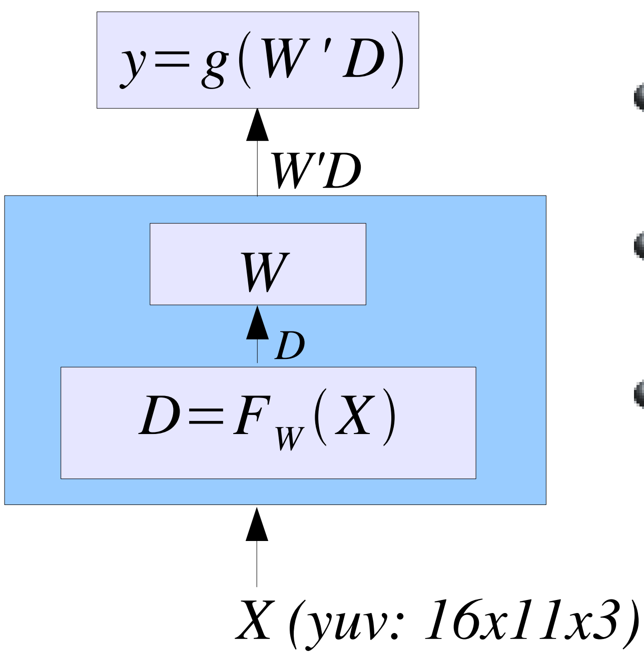
Online Learning

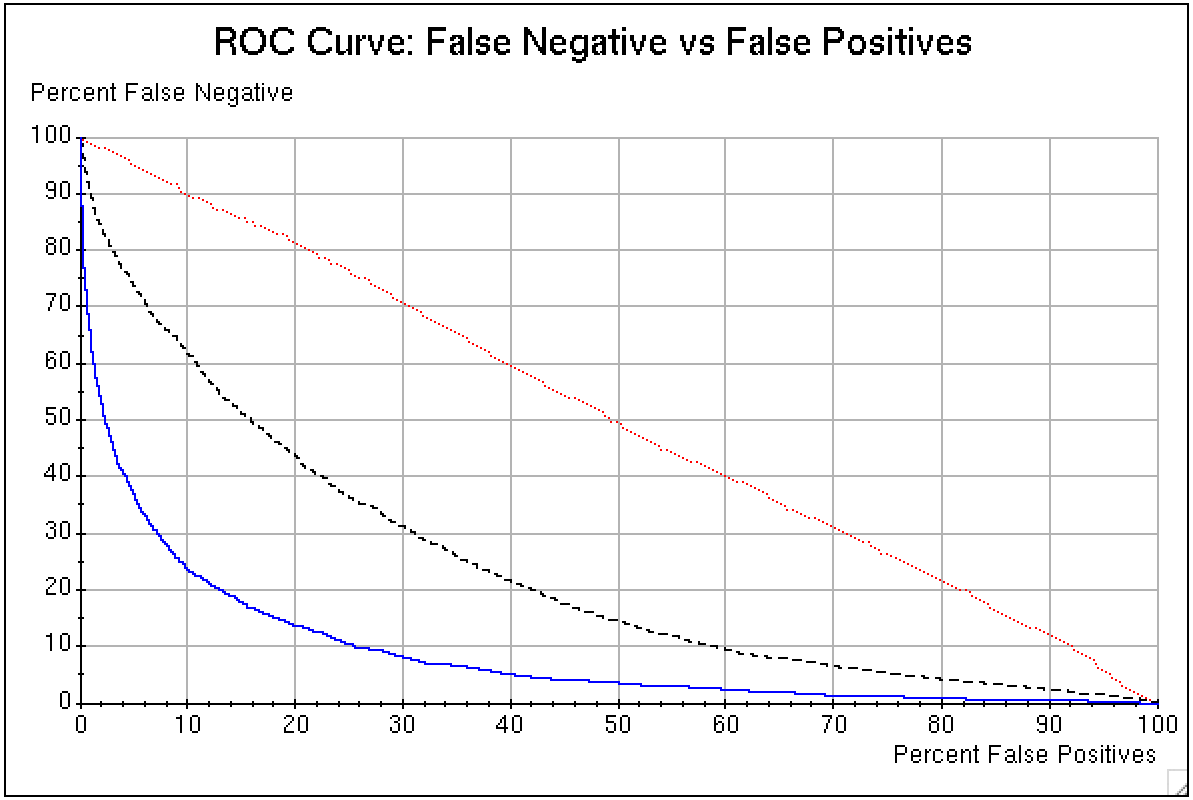
- Classifier:
  - trained online on each frame using gradient descent
  - Output of convolutional network: feature vector D (120 components)
  - Weights W are a logistic regression
  - Regularization: decay to default weights, L2 regularization



- Loss: $L = -\sum_{i=1}^{n} \log(g(y \cdot W'D)) - \alpha R(W)$
- Learning: $\dfrac{\partial L}{\partial W} = y \cdot g(-y \cdot W'D) D$
- Inference: $y = g(W'D)$

where: $g(z) = \dfrac{1}{1+e^{-z}}$

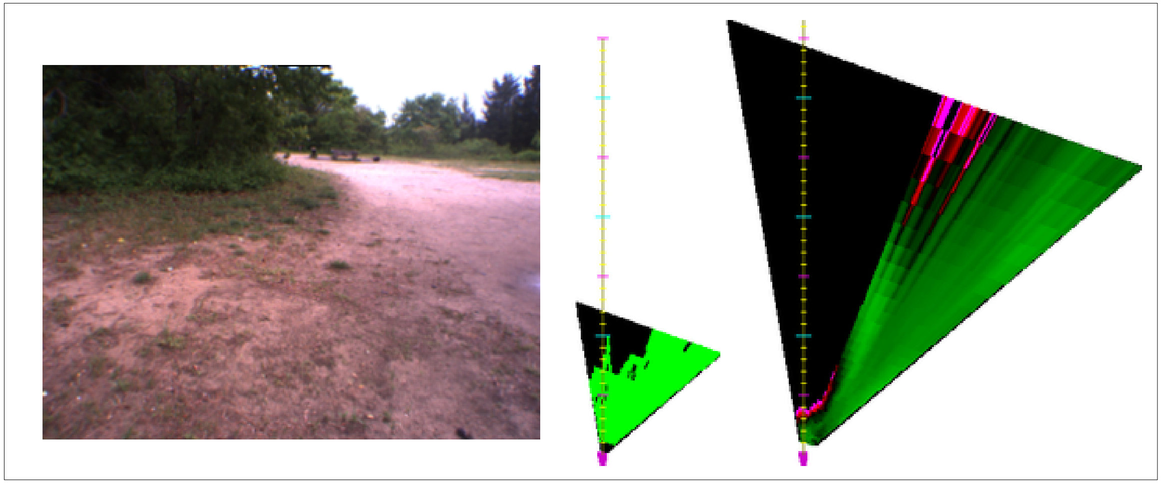
Online Learning Comparison



- Red: uninitialized weights
- Black: default weights, no online learning
- Blue: default weights, online learning

LAGR long-range vision Results

a



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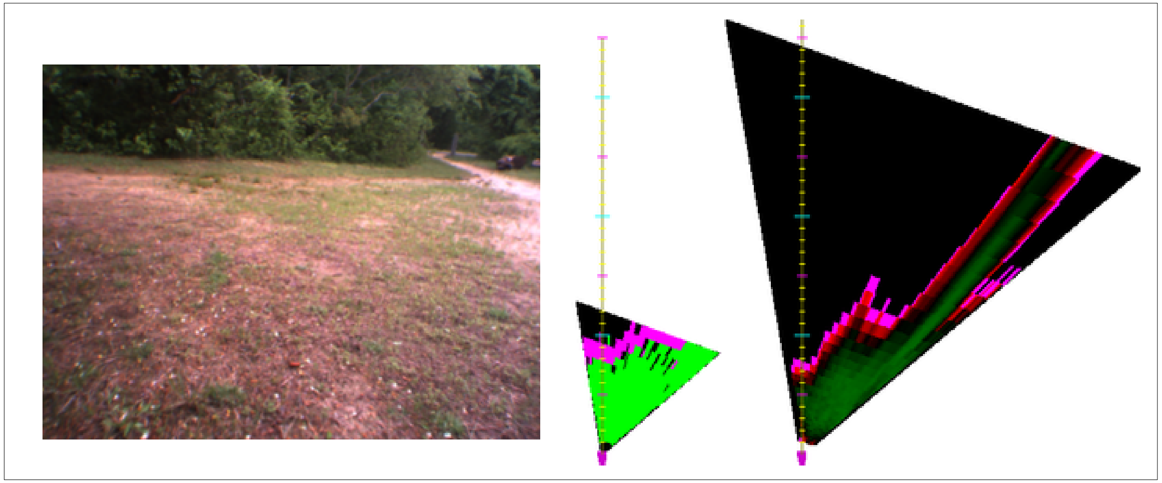

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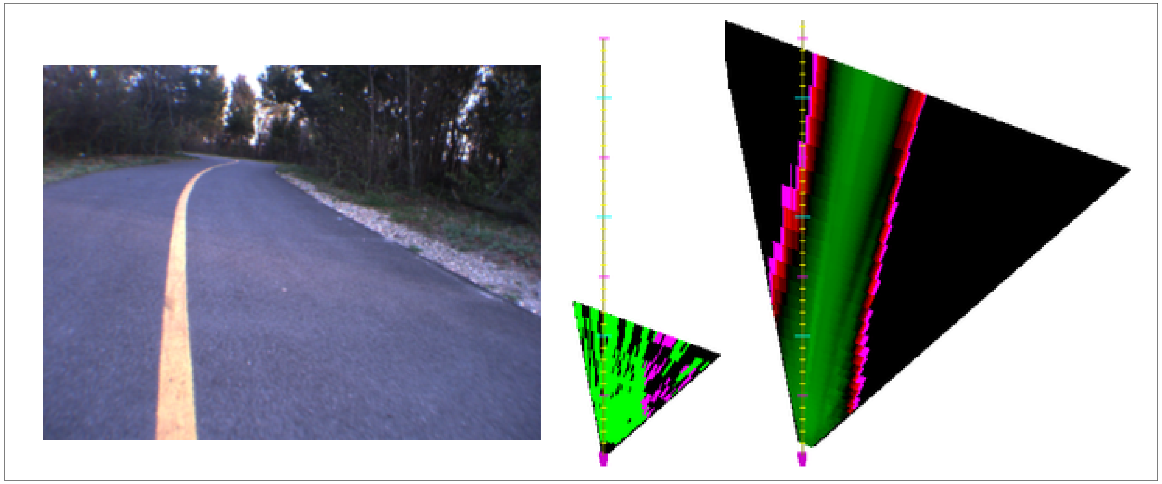

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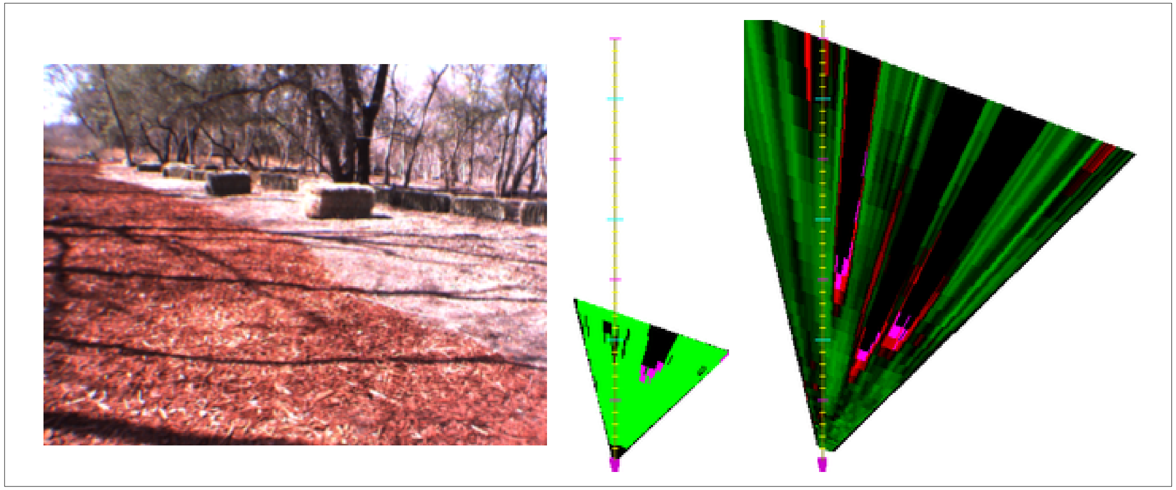

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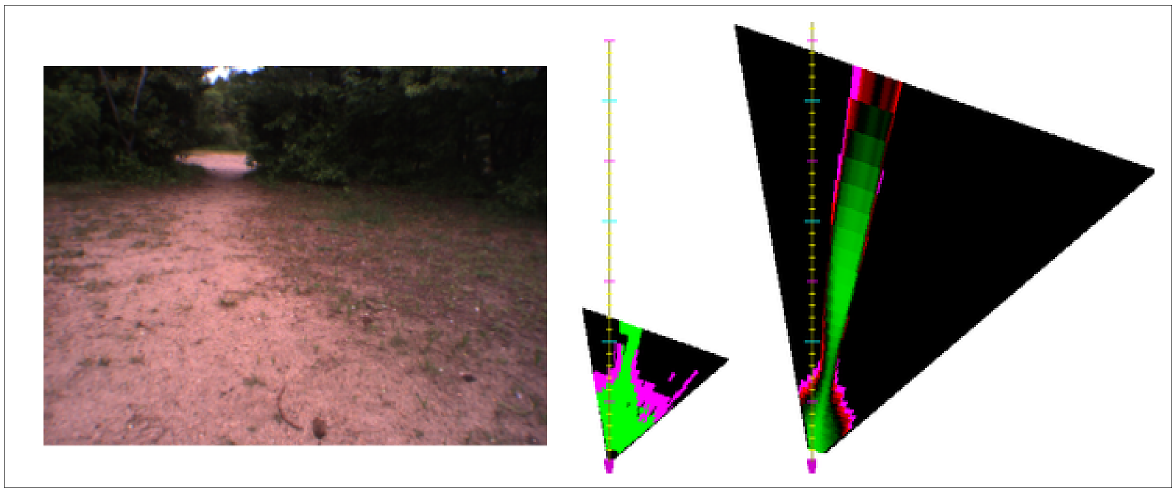

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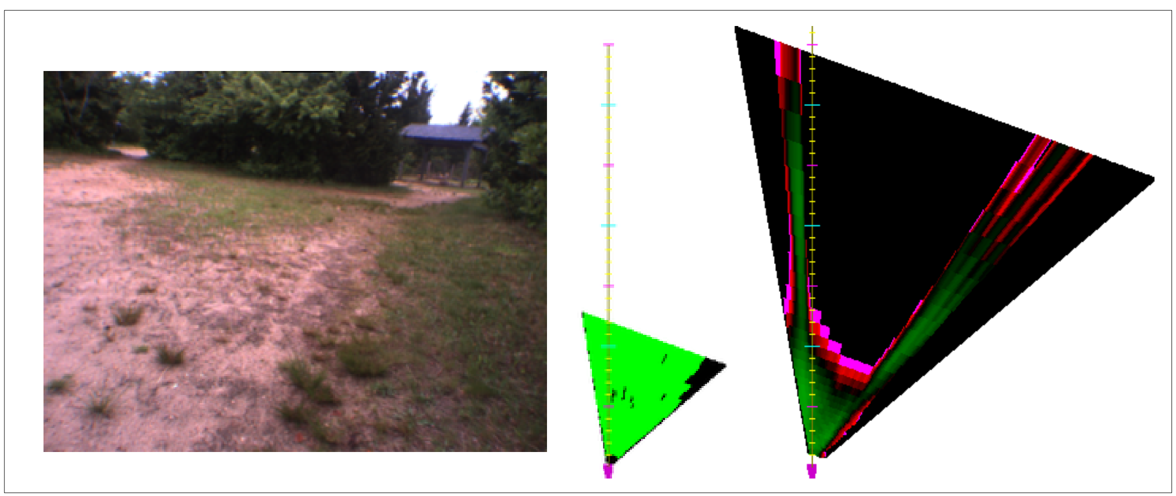

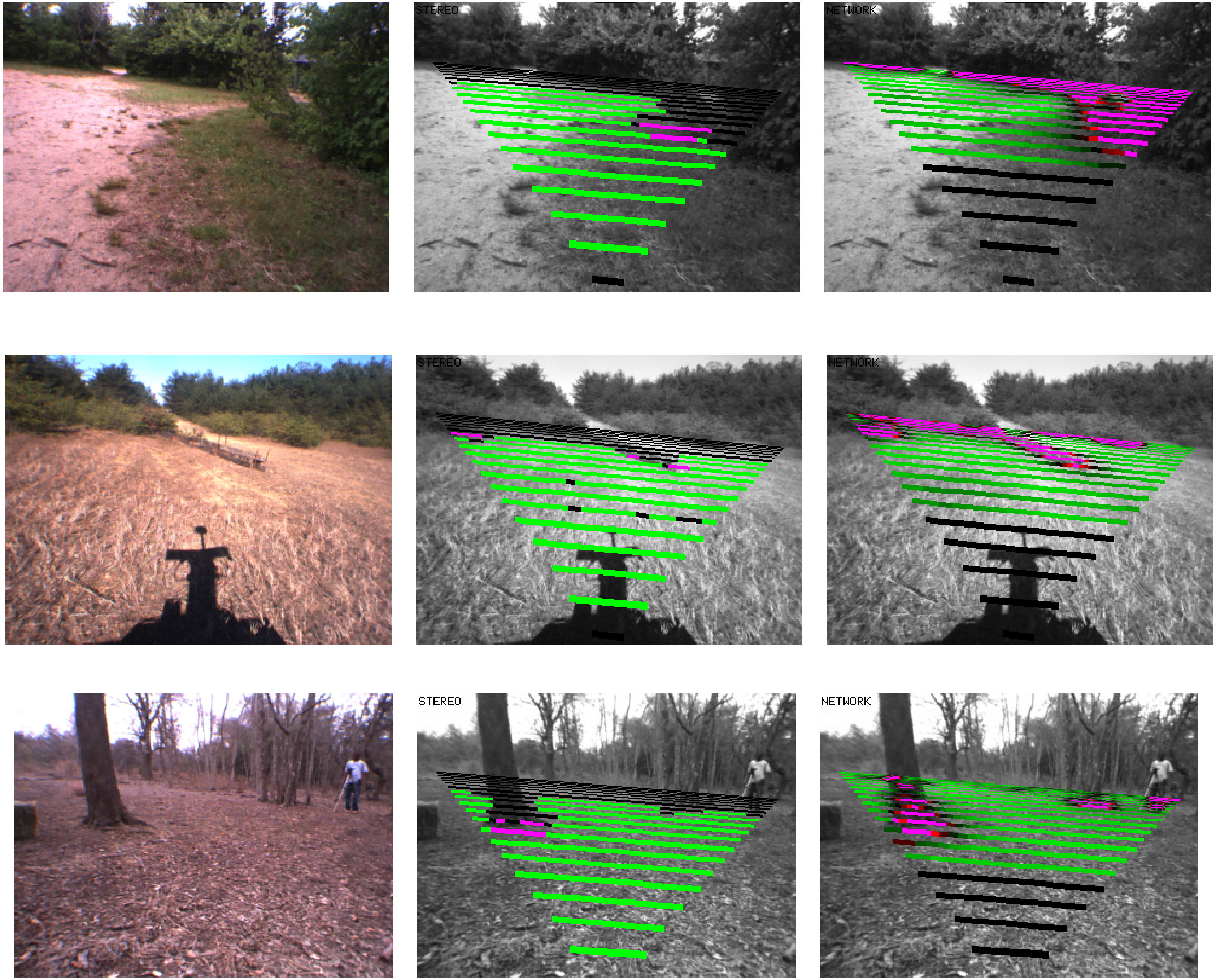
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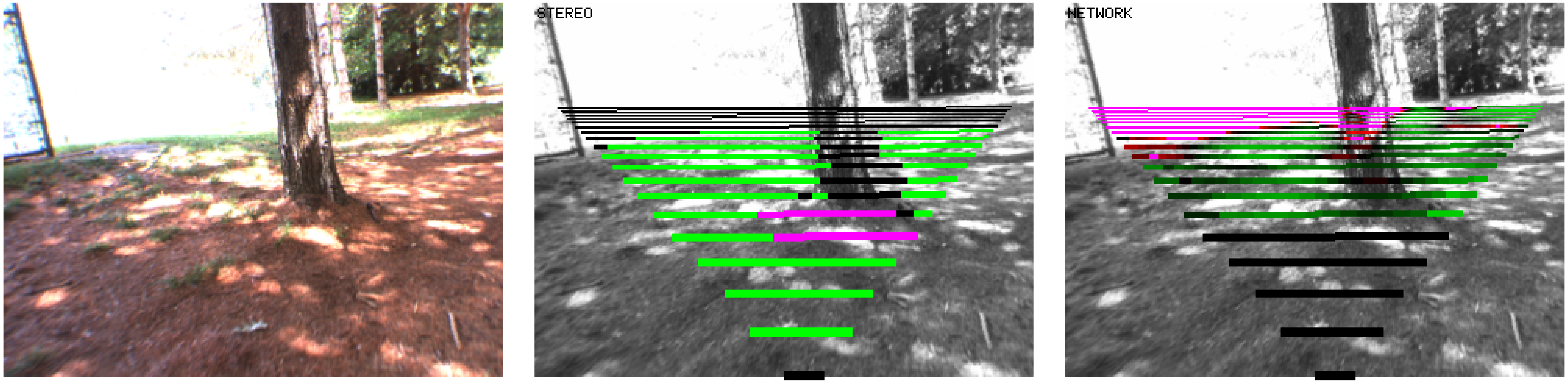
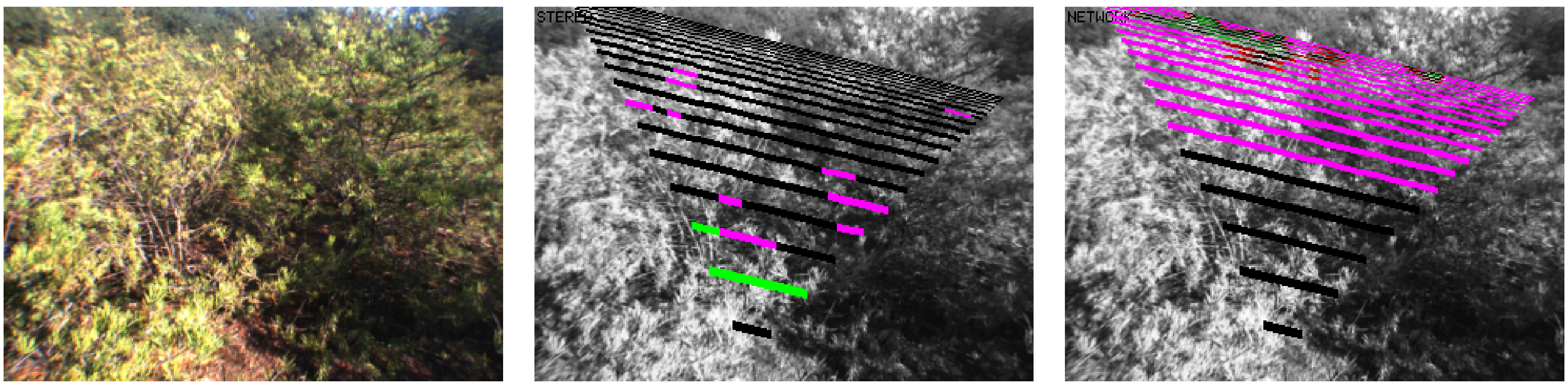
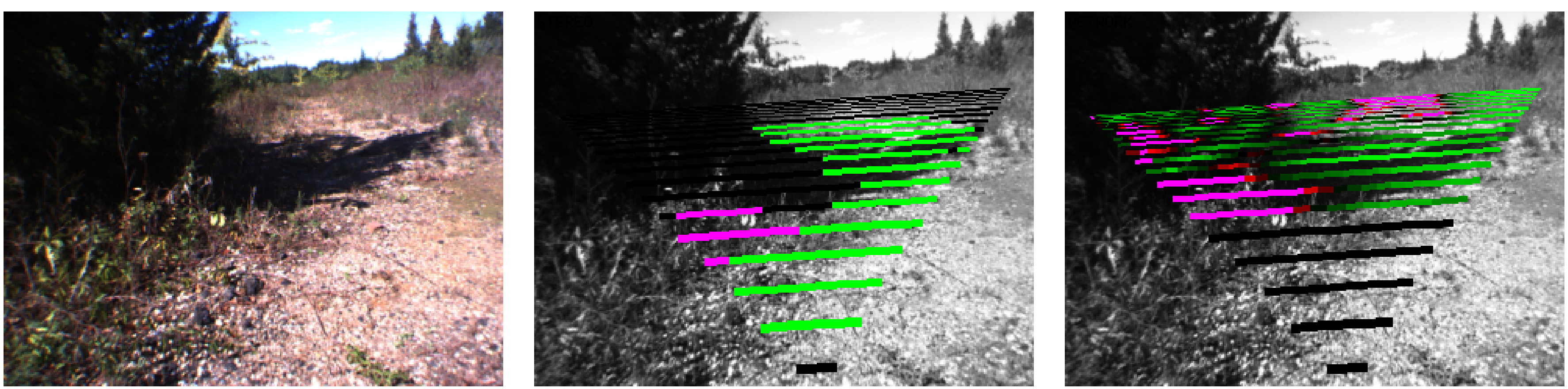


Failure mode: saturated area is mis-classified



Failure mode: bad ground plane estimate



Failure mode: poor short term memory leads to erratic classification

In Summary

- Long Range Vision on LAGR platform:
  - Near-to-Far **online** learning
    - we use **context-rich image windows**, not color histograms
  - Distance-normalized image pyramid
  - Spatial label propagation
  - **Convolutional network** for feature extraction
  - Runs at 4-5 hz
  - Smooth, accurate maps **5 to 35 meters**
- Caveats
  - Range estimates can be very poor (ground plane estimation)
  - Glare, close obstacles, tall grass/scrub (poor stereo labels)
  - Desperate need for visual odometry to correct positioning errors