

# Vision-Based Trail Following

**Dynamic Vision Laboratory** Dept. Computer & Information Sciences University of Delaware, USA

# The Appearance Variability of Trails



# Cues for Trail Finding

- Treat the trail region as an object, like a person or car, that we are trying to detect in the image
  - This is a classic computer vision problem
  - Shape here means position, scale, orientation, curvature—actually fewer parameters than many other classes of object
- A machine learning approach would be to train on trail examples
- Full range of gestalt cues are available, but which are most valuable?

# Visual Appearance Cues Light/dark: Known *a priori*, or just based on local contrast?





### Visual Appearance Cues

 Color: Helps with discrimination, but more complicated to define similarity, especially with variable illumination

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### Visual Appearance Cues

Color: Single color may not adequately describe trail region—how to compare mixtures of colors?





# Visual Appearance Cues Texture: Homogeneity vs. heterogeneity, isotropy vs. anisotropy





A problematic case...

### Visual Appearance Cues

 Gross shape: Trails taper from bottom to top, nearby sides are nearly straight → triangular under perspective



### Structural Cues

- Regardless of scene appearance, bottom line is that we don't want to run into obstacles
- If we're lucky, obstacles will actually delineate the trail
  - Look for height contrast or variance as trail's distinguishing feature?







# Structural Cues: From Where? Laser range-finder (aka ladar/lidar)



Velodyne \$60K



# Structural Cues: From Where?Laser range-finder (aka ladar/lidar)



SICK LMS \$5K



# Structural Cues: From Where?Stereopsis (static or motion-based)



Left image (undistorted)



Left and right images overlaid as red & blue channels

**Field** 

# Structural Cues: From Where?Stereopsis (static or motion-based)



Left image (undistorted)



**Estimated depth** 

Field

# Structural Cues: From Where?Stereopsis (static or motion-based)



Left image (undistorted)



**Estimated depth** 

Forest

# **Cues for Trail Finding**

- Treat the trail region as an object, like a person or car, that we are trying to detect in the image
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  - Shape here means position, scale, orientation, curvature—actually fewer parameters than many other classes of object
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- Full range of gestalt cues are available, but which are most valuable?
- What about the top-down vs. bottom-up question?

# Histogram-based Trail Following

#### Very bottom-up approach:

- Assume sides of image are off-trail
- Build histogram of colors of off-trail pixels (yellow boxes)
- Classify remaining image pixels as trail/non-trail based on likelihood given by histogram
- Median x coordinate of trail pixels is trail center

Adjust off-trail boxes



# Shape-Guided Superpixel Grouping (IROS 2008)

 Another bottom-up method, but at higher level
 Superpixels (Felzenszwalb, 2004; Malik, 2001) are pixels clustered by proximity and color similarity









Felzenszwalb

Malik

# Shape-Guided Superpixel Grouping (IROS 2008)

- Preprocess image into superpixels
- Repeatedly generate randomized groupings of superpixels as trail hypotheses
- Choose mostly likely grouping based on weighted combination of
  - Shape likelihood: How "triangular" is grouping?
  - Appearance likelihood: How strongly does color inside grouping contrast with colors of neighboring superpixels?
  - Deformation likelihood: Are overall size, width-to-height ratio, etc. of fitted triangle in expected ranges?





# Shape-Guided Grouping Results



























# Triangular Trail Regions (IROS 2009)

- Approximate trail boundary viewed under perspective as triangle T with bottom side defined by image bottom
- To measure contrast, look at equal-width triangular neighbor regions  $T_L$  and  $T_R$



#### Trail region appearance characterization

- Compute color features (aka *textons*) via *k*-means clustering in CIE-LAB space (following Blas, 2008)
  In a sense this is like superpixels without proximity
  Clustering done over 3 different feature sets (these
  - are used for feature switching)
    - AB (chromaticity only)
      - L (brightness only)
    - LAB (full color space)

Model trail region T's color distribution via texton histogram  $H_{\tau}$ 



# Trail likelihood function

Weighted sum of measures of:
 Color/brightness contrast of center trail region with neighboring regions
 Quantify similarity using standard histogram metric of chi-squared distance χ<sup>2</sup>
 Homogeneity of trail region—the fewer colors, the more likely
 Quantify heterogeneity with entropy of histogram

 $L_{appear}(T) = \alpha[\chi^{2}(h, h_{L}) + \chi^{2}(h, h_{R})] + \beta(1 - H(h))$ 

### Likelihood maximization and tracking

- Find and track good trail candidates via MAP estimation using particle filtering
  - For static images, trail estimate is likelihood particle found after t iterat
     For image sequences, state is sum
  - of particles weighted by their likelihoods
  - Small fraction of particles are sampled from image-wide prior (rather than near previous state)



### Experimental Results – Sample Images



For display, feature set selected is indicated by color of fitted triangle: LAB = red, AB = green, L = blue

# **Omnidirectional Trail Following**

- Triangle approach works visually, but results cannot easily be translated into robot coordinates
  - IGVC 2008 showed that camera with narrow field of view was very limiting
- As with IGVC 2009, calibrated omnidirectional camera allows for trail shape hypothesis to be expressed in robot rather than image coordinates
- Don't have to process whole image—just "look" where you need to



# 4-D Omnidirectional Trail State







Width
 Curvature
 Lateral offset
 Heading error



LAB textons

**AB** textons

# **Omnidirectional Motion Planning**













Left camera view

Right camera view



# Ongoing Work

 Combine structural information (ladar + stereo) with appearance in trail likelihood function



 Visual odometry for obstacle registration and map creation







Feature triangulation and robubliction integration and accumulation 3-D motion estimation of obstacle observations in global map

Incorporate trail color model into tracked state

# Stereo + visual odometry



Stereo depth estimation for small & negative obstacles

Optical flow for visual odometry