

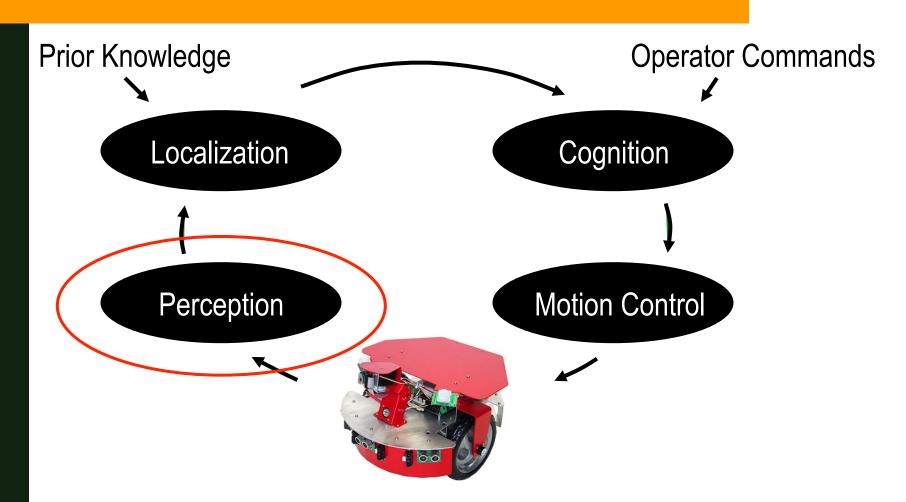
COS 495 - Lecture 10 Autonomous Robot Navigation

Instructor: Chris Clark Semester: Fall 2011

Figures courtesy of Siegwart & Nourbakhsh



Control Structure



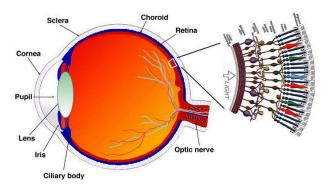


Outline

- Vision Systems
 - 1. Introduction
 - 2. Stereo Vision
 - 3. Optical Flow
 - 4. Color Tracking



- Vision is our most powerful sense. It provides us with an enormous amount of information about the environment without direct contact.
 - Millions photoreceptors
 - Sample rate of 3 Gbytes/s
 - 60 Billion neurons used to process an image



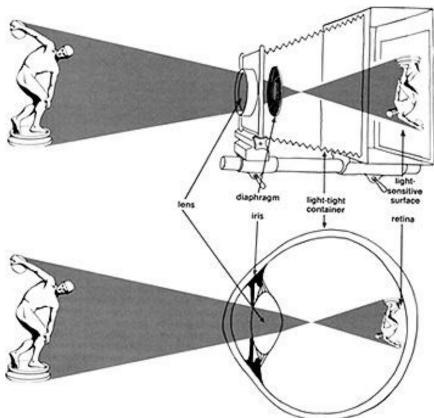


- Our visual system is very sophisticated
- Humans can interpret images successfully under a wide range of conditions – even in the presence of very limited cues





- Not sensible to copy the biology, but learn from it
 - Capture light
 - Convert to digital image
 - Process to get "salient" information





 There exist a large number of cameras capable of getting these images...





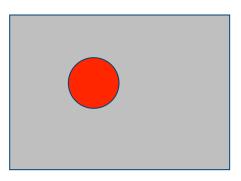
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Sensors: Vision Systems

- Monocular Vision:
 - Problem with monocular vision is that you can't tell how far something is from the robot. No Range information!
 - Consider the following image of a red ball:

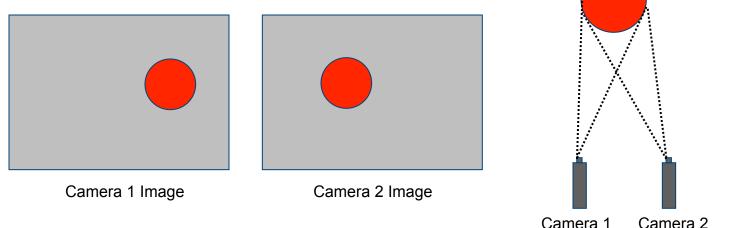


 Depending on the size of the ball, it could be located closer (position 2) or farther (position 1) from the camera



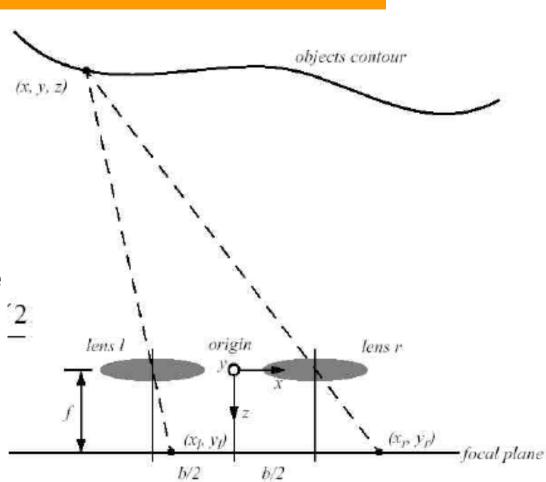
Sensors: Vision Systems

- Stereo Vision:
 - Using two cameras provides enough information to give us the range to the ball
 - The intersection of the two cones must be where the ball lies.

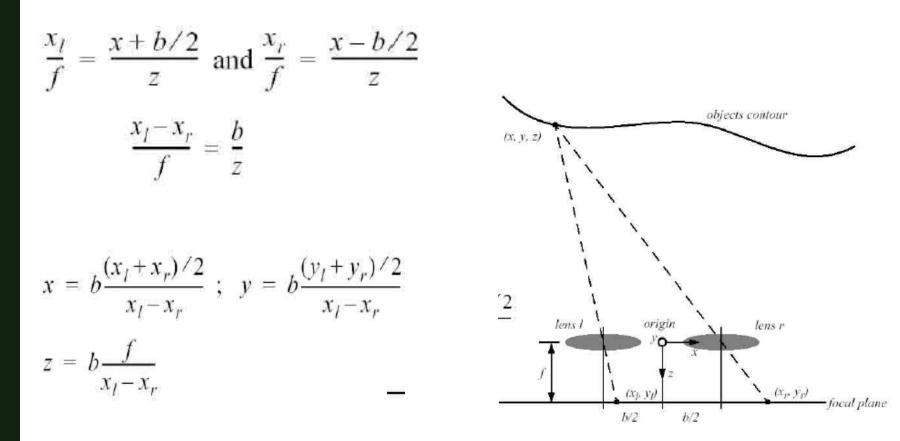




- Consider idealized camera geometry
- Compare projection of a target on 2 image planes.









- There is poor accuracy on far objects.
 - Farther objects have less disparity (x₁-x_r), making it difficult to get accurate depth measurements.
 - This is similar to having cameras colocated so that the object appears to be at the same position in both images. This ends up working like monocular vision



- Can we tell the difference between something 100 meters away and 101 meters away given our f = 0.1m and b=0.5m?
 - The disparity for z = 100 is (0.1)(0.5)/100 = 0.0005
 - The disparity for z = 101 is (0.1)(0.5)/101 = 0.000495
- How about the difference between something 10 meters away and 11 meters away?
 - The disparity for z = 10 is (0.1)(0.5)/10 = 0.005
 - The disparity for z = 11 is (0.1)(0.5)/11 = 0.0045
- We can see there is greater difference between the disparities when the object is close, so...
- Easier to get accurate range when the object is closer!



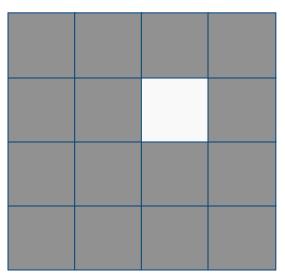
- Disparity is proportional to b
 - Want large b to get larger disparity and better accuracy.
 - But, we need to objects in field of view of both cameras.
 - Hence there is a trade-off between large b for greater disparity (and hence better accuracy), and keeping objects in the field of view of both cameras.



- Key issue is the correspondence problem
 - Identifying same feature from two cameras
- "Zero crossing of Laplacian of Gaussian (ZLoG) is widely used method of identifying feature from 2 images
 - "brightness" = image irradiance *I(x,y)*



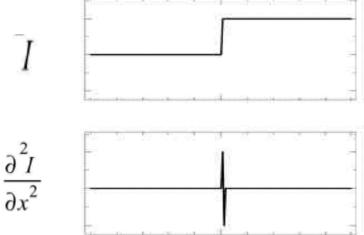
- Consider the 4x4 image:
 - I(i,j) = 0.8 if i=3, j=3
 0.1 else
 - Let's see how we can identify the bright spot





 ZLOG method finds features with high intensity contrast as measured by Laplacian.

$$L(x, y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}$$



The zero-crossing indicates a feature!



- To implement the Laplacian, an approximate function is used.
 - The convolution with P:

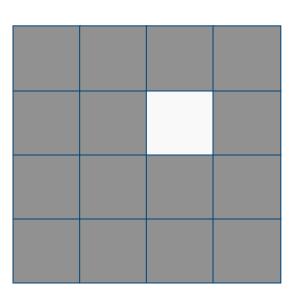
$$L = P \otimes I \qquad P = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

 That is, each pixel of L is made by summing over adjacent pixels:

L(i,j) = I(i-1, j) + I(i+1, j) + I(i, j-1) + I(i, j+1) - 4I(i, j)



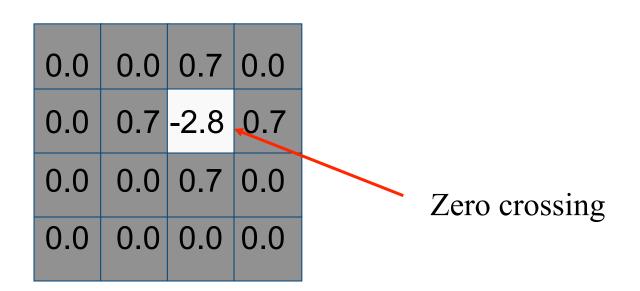
- Apply the Laplacian to our 4x4 image:
 - L(3,2) = 0.1 + 0.1 + 0.1 + 0.8 4 (0.1) = +0.7
 - L(3,3) = 0.1 + 0.1 + 0.1 + 0.1 4 (0.8) = -2.8





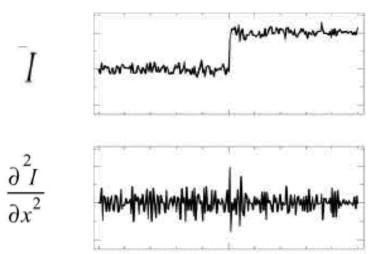
Apply the Laplacian to our 4x4 image:

- L(3,2) = 0.1 + 0.1 + 0.1 + 0.8 4 (0.1) = +0.7
- L(3,3) = 0.1 + 0.1 + 0.1 + 0.1 4 (0.8) = -2.8





 There is a problem that noise makes it difficult to detect zero crossings.



 To deal with this we use a gaussian operator to smooth/blur the image.



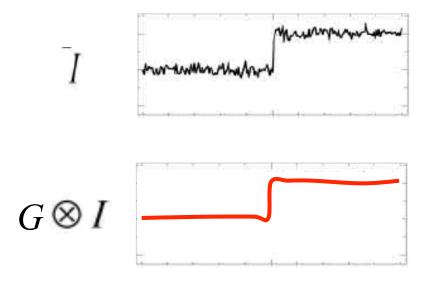
 To deal with noise we use a gaussian operator to smooth/blur the image.

> filtering through Gaussian smoothing

$$G = \begin{bmatrix} \frac{1}{16} & \frac{2}{16} & \frac{1}{16} \\ \frac{2}{16} & \frac{4}{16} & \frac{2}{16} \\ \frac{1}{16} & \frac{2}{16} & \frac{1}{16} \end{bmatrix}$$



- The Gaussian operator looks like an operator that averages the pixel values
- This has the effect of smoothing the curve:





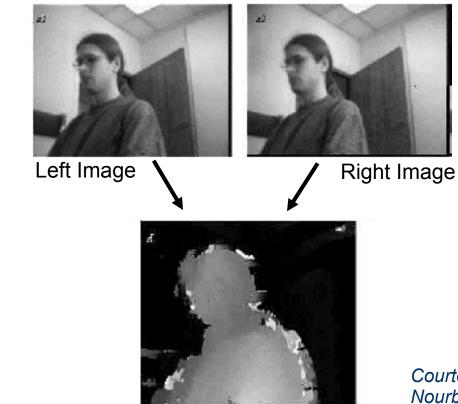
 Apply the Gaussian operator to the image will blur/smooth it so that zero-crossings will not occur simply due to noise.



- ZLog Method:
 - 1. Gaussian Filter
 - 2. Laplacian Filter
 - 3. Mark features as zero crossing
 - 4. Use geometry to recover depth map



ZLog Method Example:



Courtesy of Siegwart & Nourbakhsh



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Sensors: Optical Flow

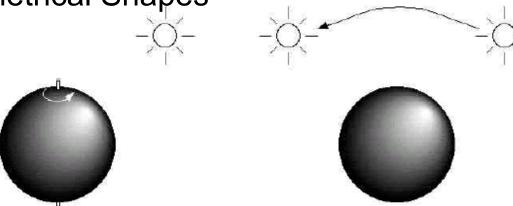
Motion Field

- A velocity vector is assigned to every point in an image.
- Given velocity of point in image, determine velocity of point in the environment.
- Optical Flow
 - Motion of brightness patterns in image.
 - Can be same motion as object motion.



Sensors: Optical Flow

- Problem: with Optical Flow is not always same as motion field.
 - Occlusions lead to discontinuities. Solution is to find these points
 - Moving Light sources
 - Symmetrical Shapes





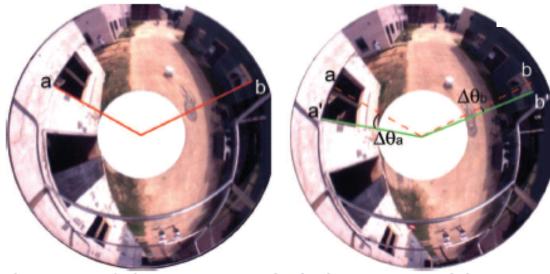
Sensors: Optical Flow for Ravine Navigation



Helicopter equipped with an OmniDirectional Camera



Regions used for optical flow calc's.



Courtesy of S. Hrabar and G. S. Sukhatme, USC



Sensors: Target Tracking Vision Systems

LED tracking



Color tracking







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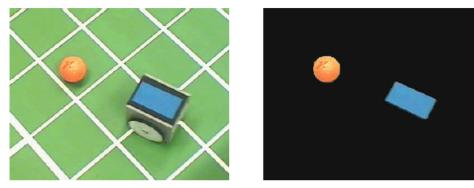
- Goal:
 - Given a color image, extract the pixels that have some specific color of interest.
 - Given the coordinates of these pixels, calculate the coloured object's position in the robot frame.
 - E.g. How do we extract the ball and robot positions from the image below?



Courtesy of EPFL STeam



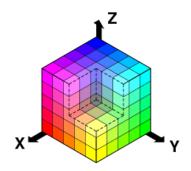
- We are given an R, G, and B value for every pixel in an image...
- Can we match these with some desired RGB values that correspond to the color of the ball and robot?



Courtesy of EPFL STeam

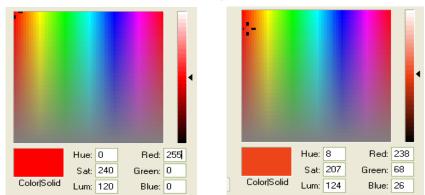


- RGB color representations assign a value from 0 to 255 to each of R, G, and B.
- These colors are additive to form white.
- Examples:
 - [0,0,255] is pure blue
 - [0,255,0] is pure green
 - [0,0,0] is black
 - [255,255,255] is white



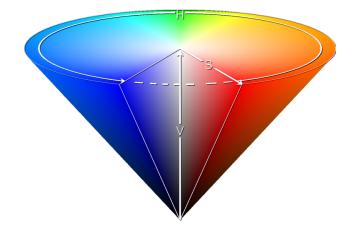


- Unfortunately, the RGB representation is not intuitive for measuring the closeness to a desired color.
 - E.g. what if we wanted to track a ball of color pure red -[255,0,0]?
 - We want to find all pixels that have values close to [255,0,0]
 - It is difficult to make good thresholds for any general color from which to accept as being close to our desired color.





- HSV color representations are more intuitive for measuring closeness:
 - Hue
 - The "color type" (such as red, blue, or yellow):
 - Ranges from 0-360 (but normalized to 0-100% in some applications)
 - Saturation
 - The "vibrancy" or "purity"
 - Ranges from 0-100%
 - Value
 - The "brightness"
 - Ranges from 0-100%





Method, for each pixel:

- Convert to HSV color space
- Determine if it is close to color being tracked by passing threshold for each parameter.

• Example:

- To track pure red, H must belong to range [350, 10], S must belong to range [80,100], and V must belong to range [80,100].
- Once all pixels that don't meet threshold are thrown out, the locations of the remaining pixels can used to determine the relative position of the object being tracked.



- MRS Example:
 - Convoy Search and Track mission