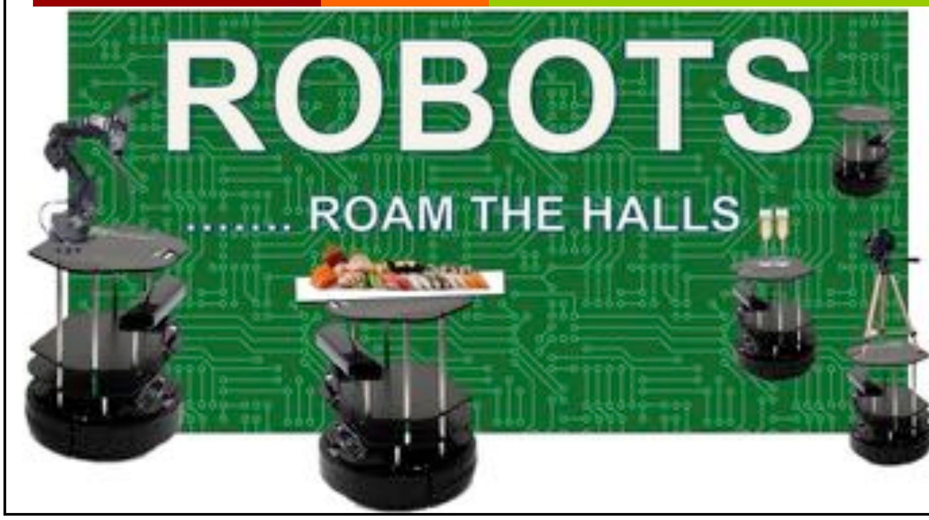
CS 189: Autonomous Robot Systems

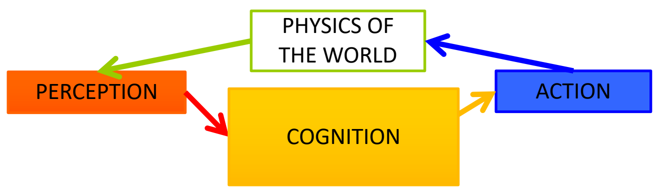
Spring 2019



Agenda

- Today's Agenda
  - Lecture: Autonomy 2: Feedback and Vision
  - Pset 2: Wanderer demonstration
- What happens next Friday?
  - **Pset 3a: Follower. Due before & in class next Friday!**
  - Pset 3b: Follower. Due week after that.
- Reading this and next week:
  - PRR Chapters 7 and 12.

What Does it Mean to be Autonomous?



Basics of Autonomy

ACTION

- Action (Actuators)
  - Locomotion: Wheels (Differential Drives, Kinematics)

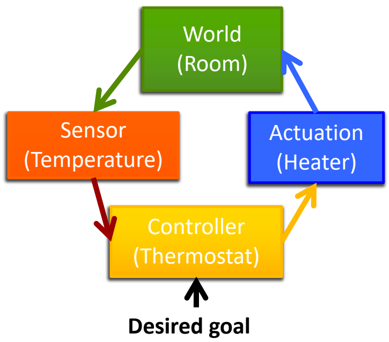
PERCEPTION

- Perception (Sensors)
  - Proprioception and Exteroception (Bumper & Depth)
  - **Today: RGB Cameras and Video**

COGNITION

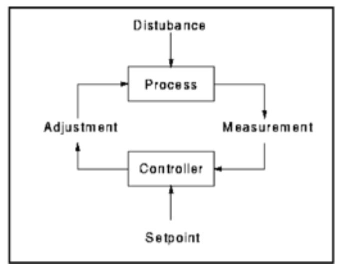
- Cognition (Control)
  - Reactive Behaviors (e.g. Roomba & Wanderer)
  - **Today: PID Controllers**

Feedback Control and PID

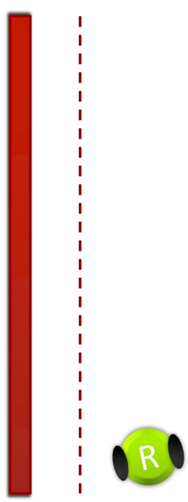


Closed Loop Control

- Desired state (goal state, setpoint)
- Feedback (i.e. measured - desired)
- Goal: MAINTAIN set-point
- *Classic Example: Thermostat*

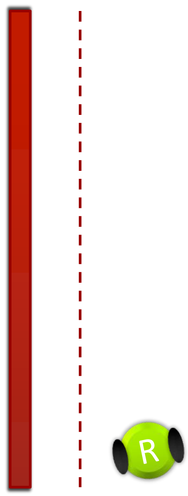


Example: Wall Following Robot



- Simple scenario: trying to move along an infinite straight wall while maintaining a fixed distance.

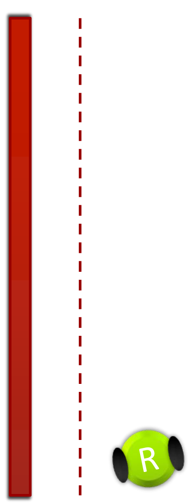
Example: Wall Following Robot



- Simple scenario: trying to move along an infinite straight wall while maintaining a fixed distance.
- **Generic Program Loop**

```
Move 1 step forward
If distance-to-wall > desired,
   Then turn towards the wall
   Else turn away from the wall
```

Example: Wall Following Robot

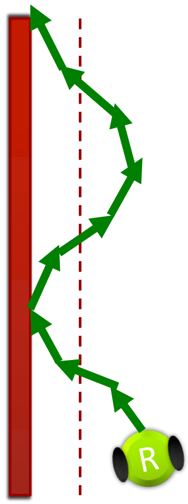


- Simple scenario: trying to move along an infinite straight wall while maintaining a fixed distance.
- **Concrete Program Loop**

```
Move 0.5 body-length forward
If distance-to-wall > desired,
   Then turn 45 degrees towards the wall
   Else turn 45 degrees away from the wall
```

- How does this Program perform?

Example: Wall Following Robot



- Simple scenario: trying to move along an infinite straight wall while maintaining a fixed distance.
- **Concrete Program Loop**

```
Move 0.5 body-length forward
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```
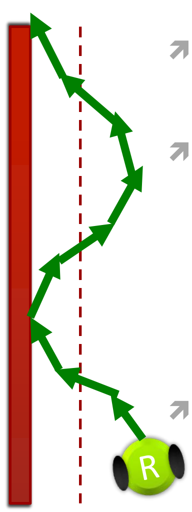

- How does this Program perform?
- How do we do better?

Example: Wall Following Robot

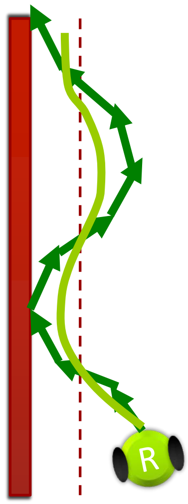


Generic Program
Move 0.5 body-length forward
if distance-to-wall is larger than desired,
  Then turn 45 degrees towards the wall
  Else turn 45 degrees away from the wall

- **How does this Program perform?**
  - Oscillates!!
- **How do we do better?**
  - Reduce turning angle to be very small (avoid overshoot)
  - Check for error very frequently (avoid overshoot)
  - Define some "slop" in our goal (range instead of exact)

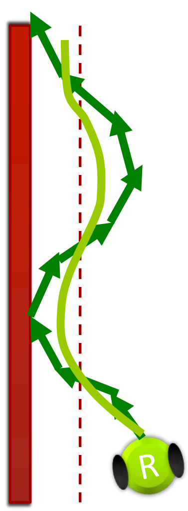
  Sometimes "bang-bang" control is enough
  (e.g. roomba using bump sensors to wall-follow)
- **How do we do even better? Use more information!**

Proportional (P) Control



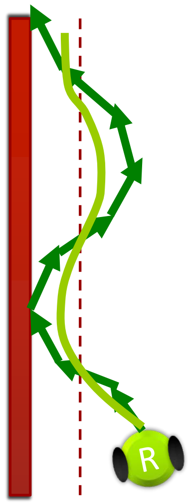
- Use more information: use both the direction and magnitude of the error to decide how to adjust.
- Error = distance-to-wall – desired distance
- Adjustment
  - ChangeAngle = Kp * error
  - Current action is just your past action + adjustment
  - Kp = “gain”

Proportional (P) Control



- Use more information: use both the direction and magnitude of the error to decide how to adjust.
- Error = distance-to-wall – desired distance
- Adjustment
  - ChangeAngle = Kp * error
  - Current action is just your past action + adjustment
  - Kp = “gain”
- High-level idea: *adjust proportional to the error*
  - If far from the Dline --- we will turn sharply
    If we are close to the Dline --- then turn very slowly
  - How do we decide what Kp is?
    Model or Experiments (Control Theory)

Proportional (P) Control



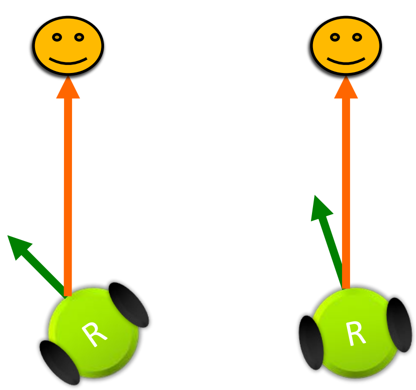
Proportional Control Program Loop

```
Move 0.5 body-length forward
If distance-to-wall > desired,
    let error = |desired – distance-to-wall|
    Then turn Kp * error towards the wall
    Else turn  Kp * error away from the wall
```

P-controllers are very useful!

New Scenario

Orient towards a "Source"



Hint: Pset 3 "Follower"

Proportional Control Program Loop

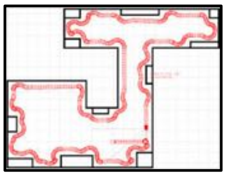
Measure error

angular-speed = k. error

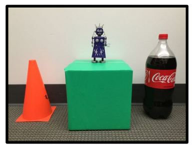
i.e. Turn faster if big angle
Turn slowly if small angle

P-controllers are very useful!

Wall Following



Visual Homing

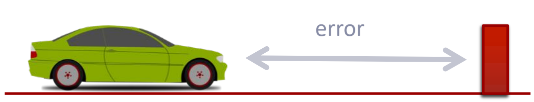


Centering

Collision Avoidance

Reactive Behaviors == Feedback Controllers

When P Control is not enough



P Controller
Loop
  Measure error
  ApplyAccelerator = k.error
  (as I get closer, I apply less gas)

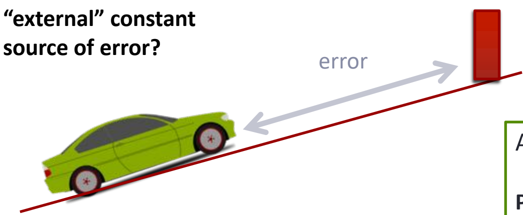
Ignores inertia!

- Momentum = mass*velocity
- Car (heavy) at 10mph vs 100mph
  - P-control only reacts to current “erro
  - But error is changing also based on s
  - Can we “predict the future change in error” => **Derivative (D) Control!**

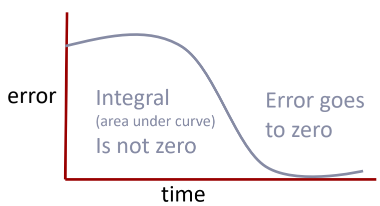
PD Controller
Loop
Measure error = distance-to-wall
Derivative-error = d(error)/dt
Change = **Kp** * error
  - **Kd * deriv-error**

When P Control is not enough

What if there is an "external" constant source of error?



P Controller
Loop
Measure error
ApplyAccelerator = k.error



Adjust based on "past failures"

PID Controller
Loop
Measure error = distance-to-wall
Derivative-error = d(error)/dt
Integral-error = sum(error + past)
Change = **Kp** * error
- **Kd** * deriv-error
+ **Ki * integral-error**

And that's PID Control!

Proportional Integral Derivative

P PRESENT **I** PAST **D** FUTURE

$$u(t) = K_p e(t) + K_d \frac{d}{dt} e(t) + K_i \int e(t)$$

P-control: In this class, we will only really use P-controllers since our robots are slow. Derivative control while important is the most complex, since derivatives tend to be noisy. Integral control is more commonly used, to get rid of persistent errors.

Setting Gains: Analytical models are hard to get accurate, but empirical tuning is often not that bad. Common method is to tune Kp first, until stable consistent oscillations, then tune D and then I. There is also a heuristic method called the *Ziegler-Nichols Tuning Method* which defines the desirable Kp:Kd:Ki ratio

Basics of Autonomy

ACTION

- Action (Actuators)
  - Locomotion: Wheels (Differential Drives, Kinematics)

PERCEPTION

- Perception (Sensors)
  - Proprioception and Exteroception (Bump, Depth)
  - **Today: More about Cameras and Color**

COGNITION

- Cognition (Control)
  - Reactive Behaviors (e.g. roomba, collision avoidance)
  - **Today: PID Controllers**

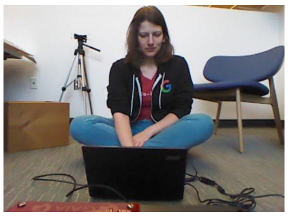
Perception: Robot Vision

Pioneer robot with stereo cameras, sonar ring, and LIDAR

- Why Robot Vision?
  - Operate in human designed world!
  - Cheaper and cheaper Cameras!
- But robots vision != computer vision
  - Robots have limited computation time and not a lot of memory *(real-time)*
  - Robots are *action driven*, and thus perception is *task driven* – can be less general *(minimalism)*
  - Robots also have the advantage (?) that they see images over and over while they move *(video)*

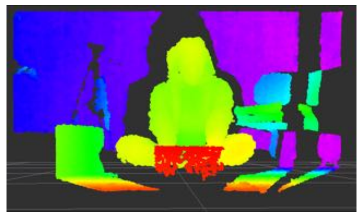
Vision: Many Options

COLOR CAMERAS



Why Object
Recognition
Is hard.

DEPTH SENSING



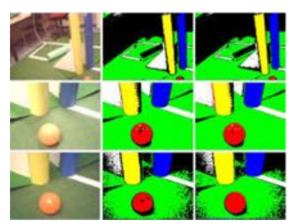
How Depth
Cameras work
& When to use

VIDEO/MOTION

Optic Flow and
Object Tracking

But First: A Video……

"James Bruce. CMU, 2001



Vision: Many Options

COLOR CAMERAS

- Object Recognition
  - Classically hard AI problem!
  - Camera gives an array of light pixels
  - How do you recognize a chair?

Task-driven Approach

- **Segmentation** (shape/color characteristics)
  - Colorspaces (HSV)
  - **Typical Style: Blur => Mask => Contours**
  - OpenCV! (real-time vision)
- **Non-Segmentation** ("features")
  - Template Matching and Histogram Backprojection
  - Classifiers ("Face Detection")
  - Fiducials (e.g. AprilTag)

Segmentation: Color Space

- Digital Camera = Array of pixels (picel == "*pic*ture *el*ement")
- **RGB**
  - 24 bit (0-255, 0-255, 0-255)
- **HSV or HSI**
  - Hue = actual color
  - Saturation = amount of color
  - Intensity = amount of light

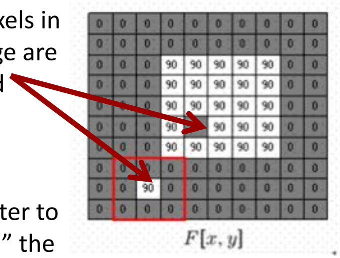
Equivalent to RGB, but easier to numerically threshold on human "meaningful" notions of color

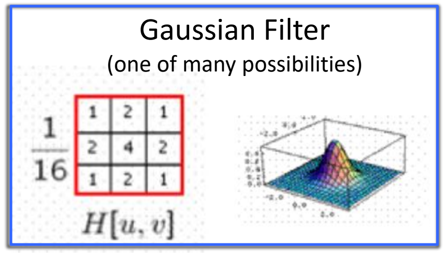
RGB	HSV
255,0,0	0,100,100
100,0,0	0,100,39.2
255,100,100	0,60,100
100,255,255	180,60,100

I can easily identify a RED (hue=0) object even if its dark or sunlight is on it!

Segmentation: Blur

Noisy pixels in the image are removed



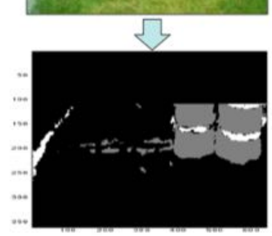


Use a Filter to "smooth" the image out

Filtering is a general concept: "apply" a matrix to every pixel

Segmentation: Blur => Mask

- **MASK == Threshold image based on "Color"**
  - Can combine masks
  - Can "Posterize" (assign color bins)



Segmentation: Blur => Mask => "Blob"

- **Give me Objects!**
  - Segment my image into "contiguous regions" of color (blob)
  - OpenCV: Find Contours – gives you a curve around each object
    (curve is represented by an array of boundary points)
  - Then you can do stuff! (boundingbox, areas)

Digression: Find Blobs Algorithm

1 0000000000000000
2 000XXX00000XXX00
3 000XXX00000XXX00
4 000XXX00000XXX00
5 000XXXXXXXXXXX00
6 000XXX00000XXX00
7 000XXX00000XXX00
8 000XXX00000XXX00
9 0000000000000000

Runs: [(2,4) to (2,6)] [(2,12) to (2,15)]
[(3,4) to (3,6)] [(3,12) to (3,15)]
..... [(5,4) to (5,15)].....
[(8,4) to (8,6)] [(8,12) to (8,15)]

Run-Length Encoding:
Find the contiguous row-regions of color of choice

```
Foreach row
    While there are still pixels in the row
        discard pixels until see redX
        record start of a "run" by (row, column)
        discard pixels until see black0
            record end of a "run" by (row, column)
```

Region Extraction
Link together the row-runs that touch in columns
Create a *directed graph* over the row-runs

List of Regions
Return a list of connected graphs ("bob") or compute a boundaries ("Bounding Box", or "Contour")

Segmentation: Blur => Mask => "Blob"

- **OpenCV libraries** make much of this very easy
  - Good documentation and online examples
  - *BUT still need lots of testing! (customize to your errors)*
- **Lab2 Solutions repository has lots of goodies**
  - Example of blur=>mask=>contours
  - Trackbar! For calibrating HSV bounds

Segmentation to Object Size

If you know the real object size,
then the image tells you how far it is!

But even better approach is to combine
RGB Camera and Depth Camera images.

Vision: Many Options

COLOR CAMERAS

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Task-driven Approach

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  - Colorspaces (HSV)
  - **Typical Style: Blur => Mask => Contours**
  - OpenCV! (real-time vision)
- **Non-Segmentation** ("features")
  - Template Matching and Histogram Backprojection
  - Classifiers ("Face Detection")
  - Fiducials (e.g. AprilTag)

Non-Segmentation Approaches

You don't need to always "recognize" the objects in your image – as the background gets more cluttered and complex this becomes hard anyways…..

- Image Signature
  - *Template matching* ("image" itself)
  - *Color Histogramming* (pixel distribution)
  - Classifiers (requires training data)
  - Cascade Classifiers (face detection)

Image Signatures

Template =
Take a closeup of the "desired" object

Match =
Image Region – Template
(sliding window, rotate template)

Output is an image of values where the lowest value is the best match
Scale/size invariance requires doing this many times.

Problem: too detail oriented

Signature =
Take a closeup of the "desired" object
Compute a Histogram of Pixel Color distributions

Match =
histogram(Image Region) – signature

Example: Robot "imprints" on an object. Then robot would moves with a speed proportional to the match…. Follows a purple triangle too…..

**OpenCV: see Template Matching, Histogram Backprojection, and Image Pyramids*

Image Signatures

Edge Detection: Sobel

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

$$|G| = \sqrt{Gx^2 + Gy^2}$$

Instead of Color you can use More Robust Features
Edge detection: (Sobel or Canny)
Corner Detection: (Harris)

SIFT = Scale Invariant Feature Detection
Do this process at many scales and rotations

Non-Segmentation Approaches

You don't need to always "recognize" the objects in your image – as the background gets more cluttered and complex this becomes hard anyways…..

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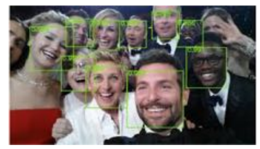

Nothing is perfect!

Non-Segmentation Approaches

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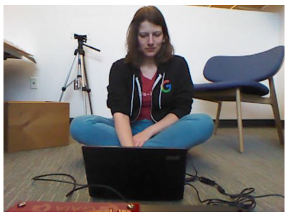
- Image Signature
  - *Template matching* ("image" itself)
  - *Color Histogramming* (pixel distribution)
  - Classifiers (Requires training data)
  - Cascade Classifiers (e.g. Face Detection)
- Fiducials
  - Place easy to recognize landmarks
  - in your environment

AprilTag System, Ed Olson, Univ of Michigan

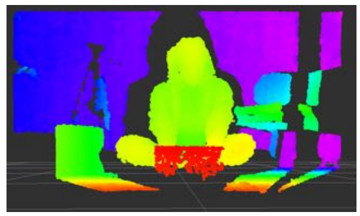
Outline

COLOR CAMERAS



Object Recognition
(segmentation vs
non-segmentation)

DEPTH SENSING



How Depth
Cameras work
& When to use

VIDEO/MOTION

Optic Flow and
Object Tracking

Video!

Motion can reveal many things!

- Background subtraction (humans move!)
- Optic flow (recover motion)
- Tracking objects

[Compare frames in RGB or Depth!]

**These slides are adapted from OpenCV tutorial (which is great reading! docs.opencv.org)*
And OpenCV provides implementations that you can use out of the box

Video!

Motion can reveal many things!

- **Background subtraction** (humans move!)
- Optic flow (recover motion)
- Tracking objects

[Compare frames in RGB or Depth!]

Basic idea – take a "window" of frames and look at all the pixels that don't change (or median pixel value). Subtract from your image…

Smarter algorithms: GMM and Bayesian models of the background

Video!

Motion can reveal many things!

- Background subtraction (humans move!)
- **Optic flow** (recover motion)
- Tracking objects

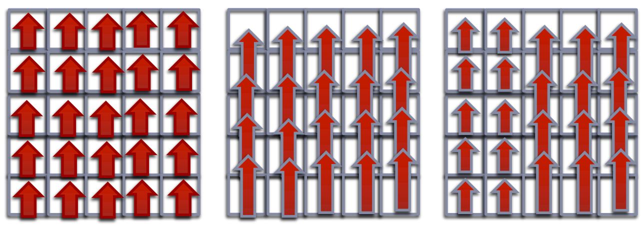
[Compare frames in RGB or Depth!]

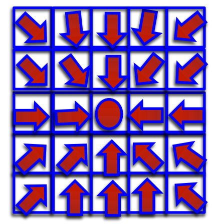
Instead of just subtraction,
Try to "track" where each pixel moved to.

Can give you SPEED and DIRECTION!
And segmentation….

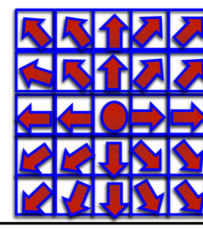
Optic Flow

Robotics! Can recover your own motion
- Speed (magnitude and direction of arrows)
- Or Distance to objects (at given speed)





Can also recover **"Behavior"**



These algorithms depend on "feature matching"
Pixel window matching (dense OF) or track features (corners/sift)

Video!

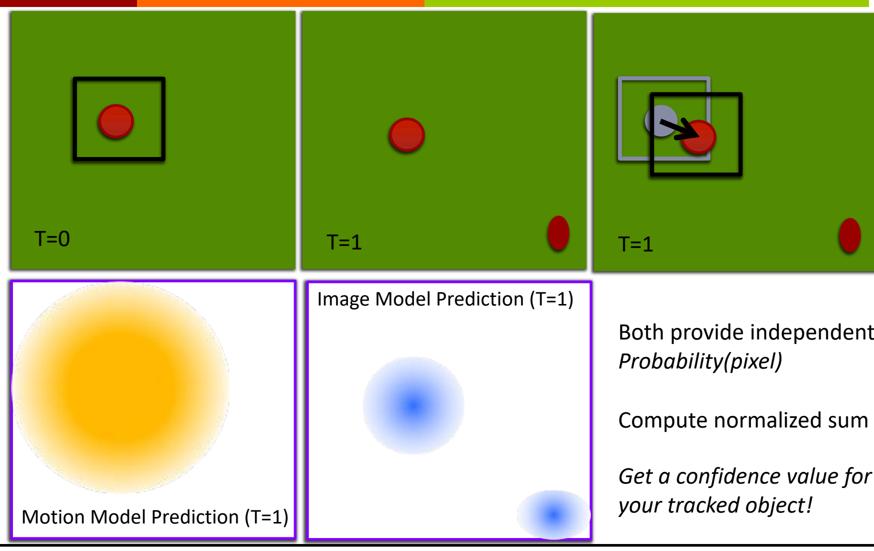
Motion can reveal many things!
- Background subtraction (humans move!)
- Optic flow (recover motion)
- **Tracking objects**

[Compare frames in RGB or Depth!]

Basic idea: Follow a "subwindow" as it moves through the image.

OpenCV: Combine **Histogram Backprojection** + **Camshift**
Later: Kalman Filter

Digression: Kalman Filter



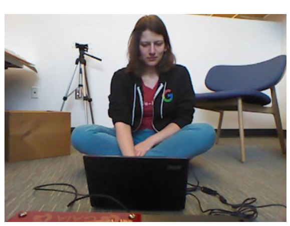
Both provide independent *Probability(pixel)*

Compute normalized sum

Get a confidence value for your tracked object!

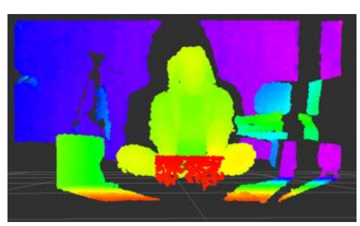
Outline

COLOR CAMERAS



Object Recognition (segmentation vs non-segmentation)

DEPTH SENSING



How Depth Cameras work & When to use

VIDEO/MOTION

Optic Flow and Object Tracking

Vision is Complex

- We still understand very little about human visual cortex
  - Much less than the eye "hardware"
- We do understand that animal vision systems use tricks
  - Bees, spiders, fish, employ many tricks that are Task Specific
  - And just good enough - not "logical" or fool proof.
- For Robots, finding appropriate tricks is critical
  - Not just for simple robots like Turtlebot
  - Google Self-Driving Car ("background substraction")
- Finally Vision is just one sensor out of many sensors we have; Choose the right sensor for the job
  - Human existence does not rely on vision – touch, balance, sound

Upcoming: Pset 3 Follower

- You have a **GREEN band** to put on your ankle
- Part 3(a) Your robot should recognize the band
  - Draw a bounding box around the ankle band
  - Try to recognize at least up to 4 feet away
  - Calibrate! ("trackbar")
- Part 3(b) Your robot should follow the band
  - **P-control** will be helpful to adjust quickly
  - Avoid running into obstacles
  - Will need to deal with quick disappearance (other leg blocks it) vs longer disappearance (robot lost you)

VIDEOS