

# Modern Product Engineering

2020

How “smart” products are created with  
sensors, algorithms and circuits

Jake Garrison

# About Me

Website: [jakegarrison.me](http://jakegarrison.me)

## Education

*Focus: Signal Processing and Machine Learning*



- **M.S. Electrical and Computer Engineering**, University of Washington, 2018
- **B.S. Electrical Engineering**, University of Washington, 2016

## Research / Job History



- **Google Health**, Research and Software Engineering, 2018-present
- **UbiComp Lab**, Mobile health researcher advised by Professor Patel, 2016-2018
- **Haiku Deck**, Software developer intern for Zuru AI feature, 2016
- **Puppy.ai App**, Founder and developer of iOS app, 2015-2018



TESLA

- **General Motors EcoCar 3**, Autonomous Driving Lead, 2015 - 2017
- **Department of Transportation**, Seattle parking load predictive modeling, 2016
- **Tesla Motors**, Sensor Integration Intern, Autopilot and Model-X Doors, 2015
- **Tesla Motors**, Power Electronics Intern, Supercharging and Insane Mode, 2014



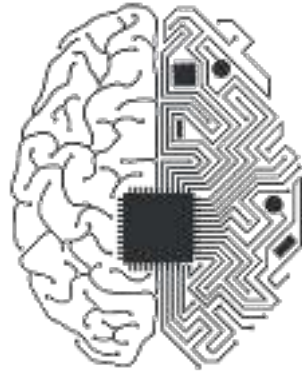
- **General Motors EcoCar 3**, Electrification Lead, 2013 - 2015
- **Verellen Amplifiers**, Built custom analog audio gear, 2012
- **Electric GTI Conversion**, highschool hobby project, 2010

# “Smart” Products

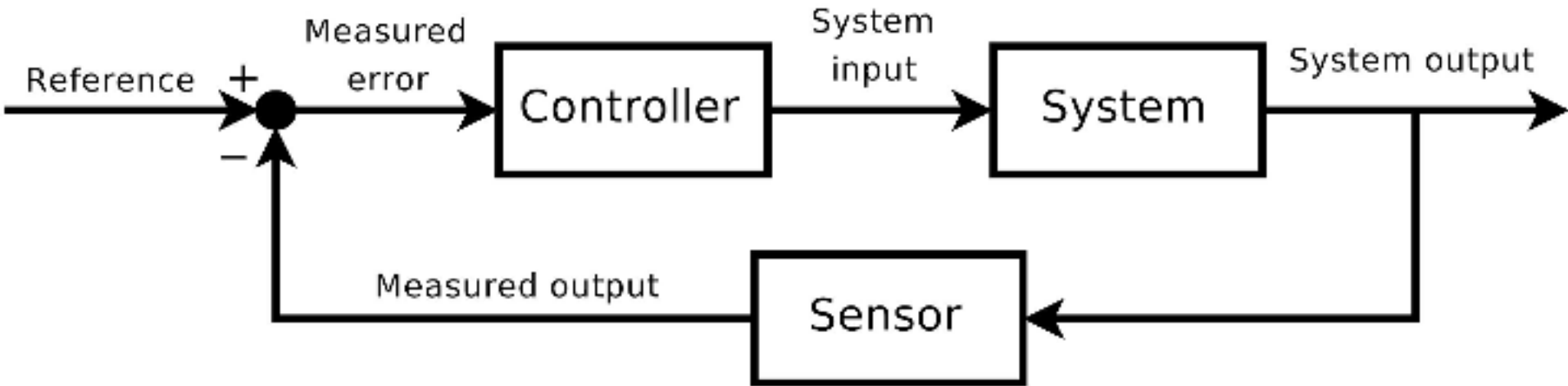
**Buzzwords: smart, intelligent, AI, autonomous, robotic**



# Control, Sensing and Processing



# Automatic Control Systems



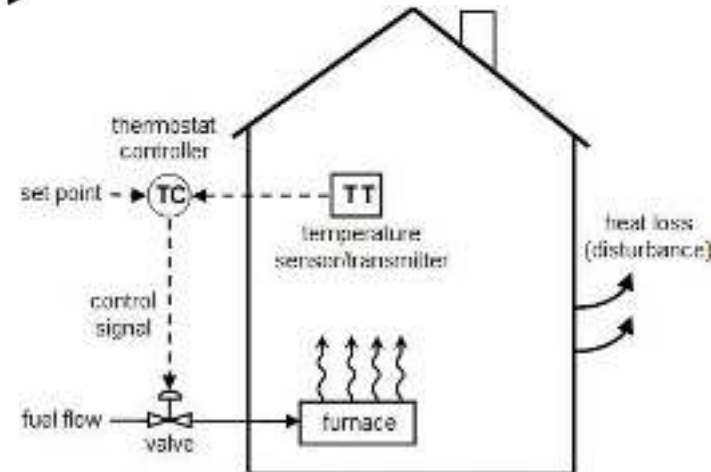
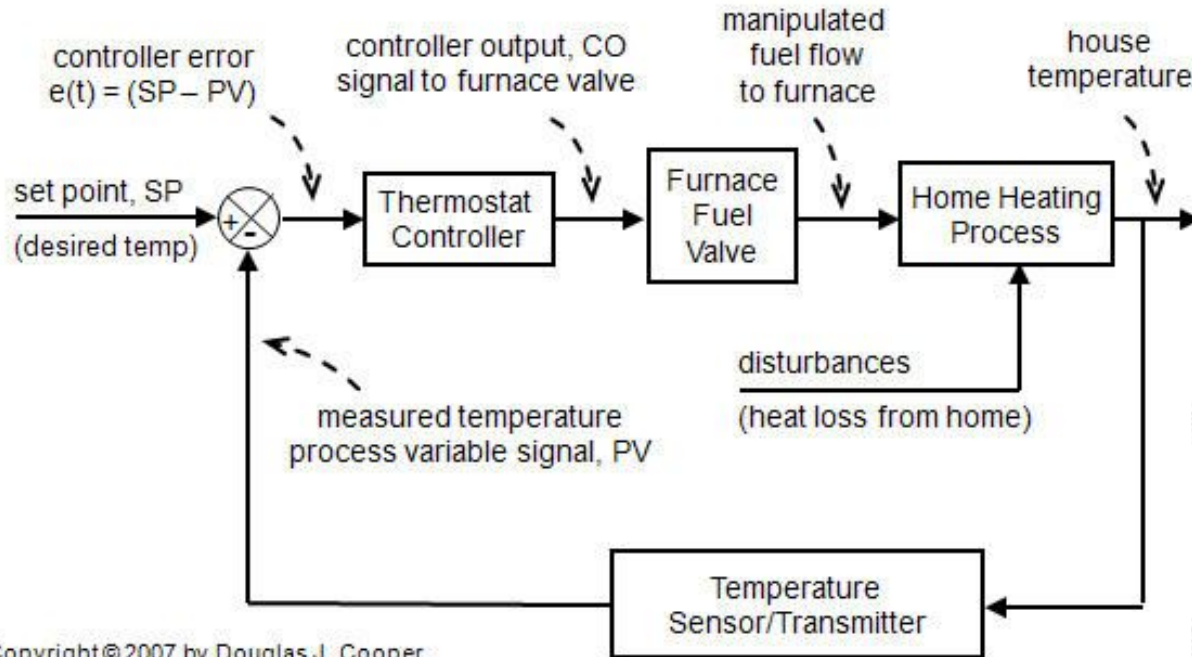


Control

# Thermostat Example

## Objectives:

(1) Keep temperature comfortable to occupants while (2) minimizing energy waste.



# Control Terminology

## Components

- **Final control element (FCE):** Actuator being controlled by (furnace switch)
- **Sensing element:** Device measuring current state of FCE (thermistor)
- **Processing element:** Circuit or chip responsible for creating control instruction (CO) given sensor inputs (thermostat controller)

## Variables

- **PV:** Process variable (house temperature)
- **CO:** Controller output signal to FCE (thermostat instruction to furnace valve)
- **SP:** Set point (temperature set on the thermostat)
- **D:** Heat loss disturbances from changing environment (outside temp)

## Closed Loop (feedback, automatic) Control

Control action from the controller is dependent on feedback from the process in the form of the value of the process variable (PV)

# Automatic Controller Objectives

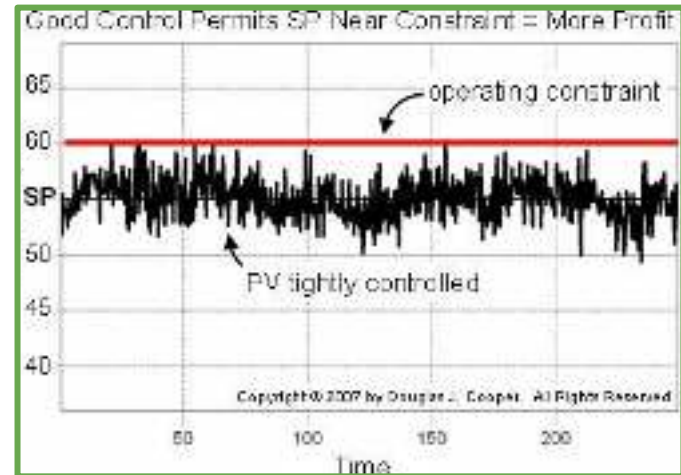
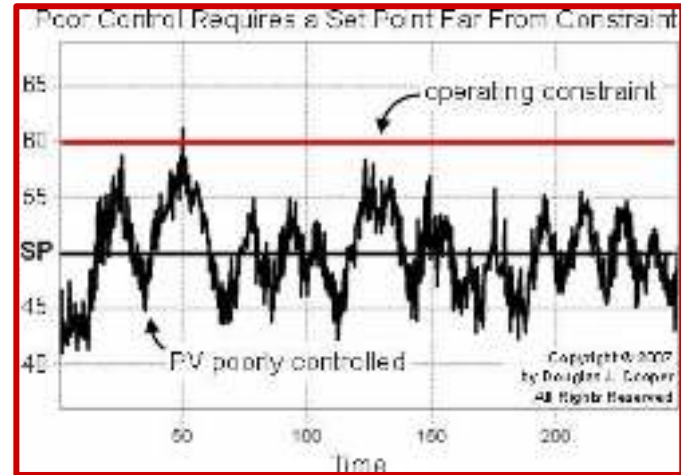
**Maintain SP despite external disturbances**

**Minimize system loss:** cost, energy, waste production, environmental impact, time spent

**Minimize system variability:** Make system more deterministic, safer.

**We want:  $PV = SP$**

Keep the measured process variable (PV) at the set point value (SP) in spite of unmeasured disturbances (D) by modulating the final control element (FCE) via controller output (CO) signal.



# Example Control Algorithm

**Error or loss, the variable to minimize via control:**

$$e(t) = SP - PV \quad (\text{error} = \text{set point} - \text{measured process variable})$$

- is the measured temp colder than set point ( $SP - PV > 0$ )? Then turn on furnace.
- is the measured temp hotter than set point ( $SP - PV < 0$ )? Then turn off furnace.
- What about when set point is hit ( $PV = SP, e(t) = 0$ )? Depends on algorithm complexity.

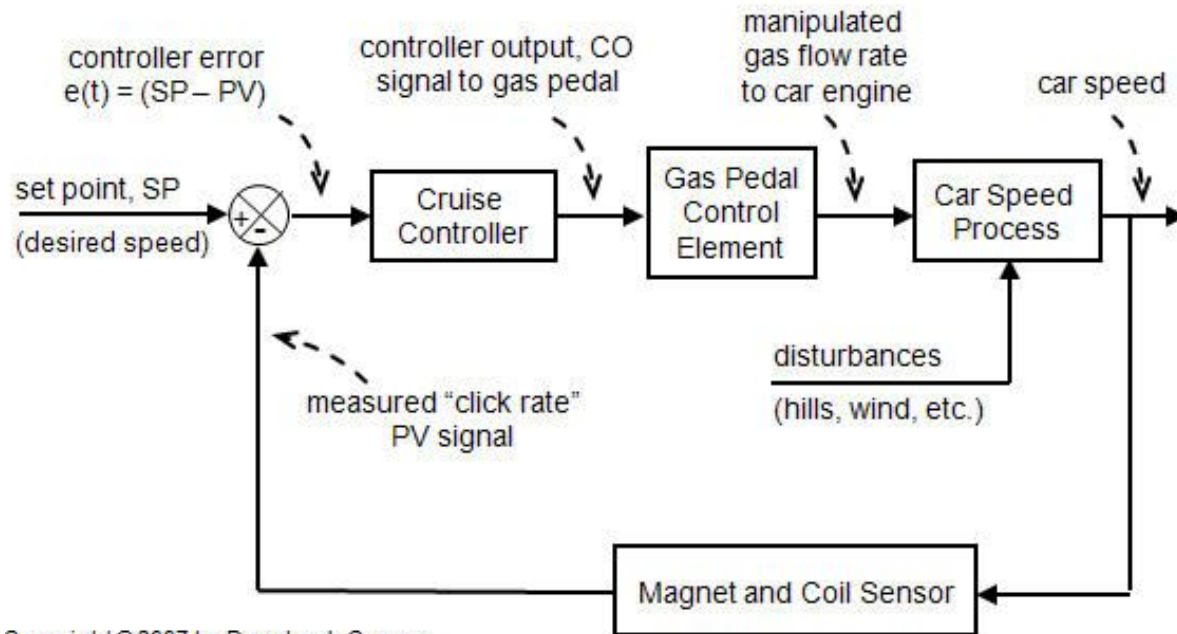
## Control Considerations

- the direction to move FCE
- how far (magnitude) to move it at this moment
- how long to wait before moving it again
- whether there should be a delay between measurement and action

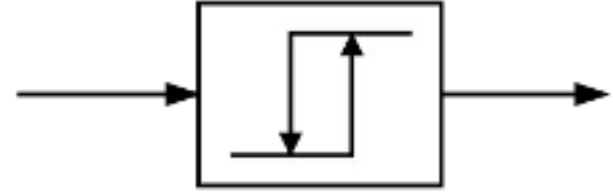
# Cruise Control Example

## Objectives:

(1) Keep speed of vehicle constant with (2) smooth braking and acceleration control.



# Bang-Bang Control



## Pros:

- Intuitive and easy to implement, two thresholds needed

## Cons:

- Oscillates around set point, rarely resulting in 0 error
- Only works with binary switching On/Off

## Algorithm:

*If  $PV > PV_{max}$ : toggle Off*

*If  $PV < PV_{min}$ : toggle On*

*Otherwise: do nothing*

## Where:

- *$PV$  = measured process variable*
- *$PV_{min}$  = lower threshold, tuned*
- *$PV_{max}$  = upper threshold, tuned*
- *$SP$  = set point*

# Proportional Control (P)

## Pros:

- Easy to tune (single parameter)
- Easy to implement (no memory needed)

## Cons:

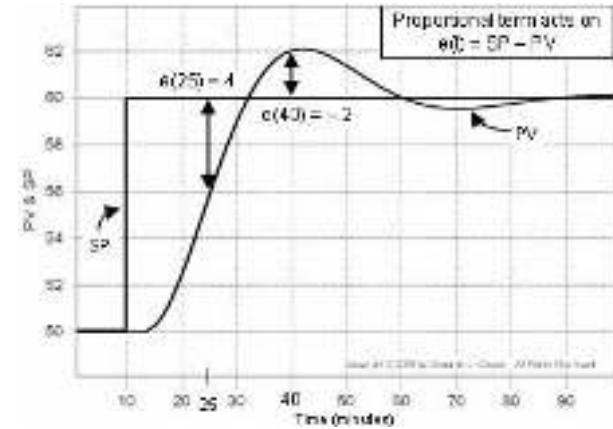
- Constant “offset” when environment slowly deviates from expectation

## Algorithm:

$$CO = CO_{bias} + K_c \cdot e(t)$$

Purpose of CO<sub>bias</sub>? (think cruise control)

Purpose of K<sub>c</sub>? (think response delay)



## Where:

- $CO_{bias}$  = controller bias
- $K_c$  = controller gain, tuned
- $e(t)$  = controller error =  $SP - PV$
- $SP$  = set point
- $PV$  = measured process variable

# Proportional-Integral Control (PI)

## Pros:

- Balance between capability and complexity
- No “offset” issue thanks to integral term acting as history driven CObias autotuner

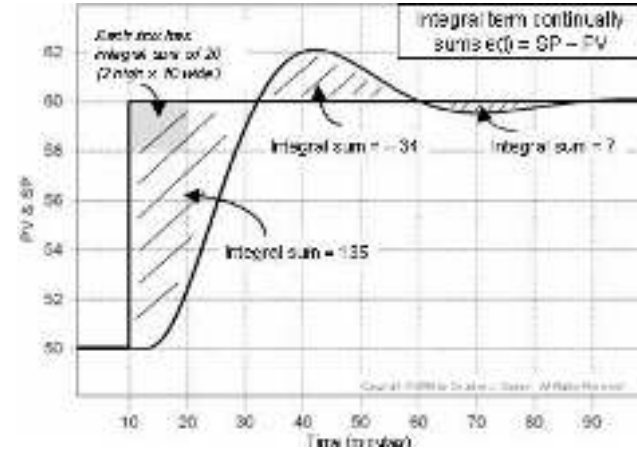
## Cons:

- Two interacting parameters are harder to tune
- Poor response to disturbances (abrupt changes)

## Algorithm:

$$CO = CO_{bias} + K_c \cdot e(t) + \frac{K_c}{T_i} \int e(t) dt$$

Purpose of integral term? (think error moving average)



## Where:

- $CO$  = controller output signal
- $CO_{bias}$  = controller bias
- $e(t)$  = current controller error
- $SP$  = set point
- $PV$  = measured process variable
- $K_c$  = controller gain, tuned
- $T_i$  = reset time, tuned

# Proportional-Integral-Derivative Control (PID)

## Pros:

- Better stability, can be used for controlling both fast and slow process variables

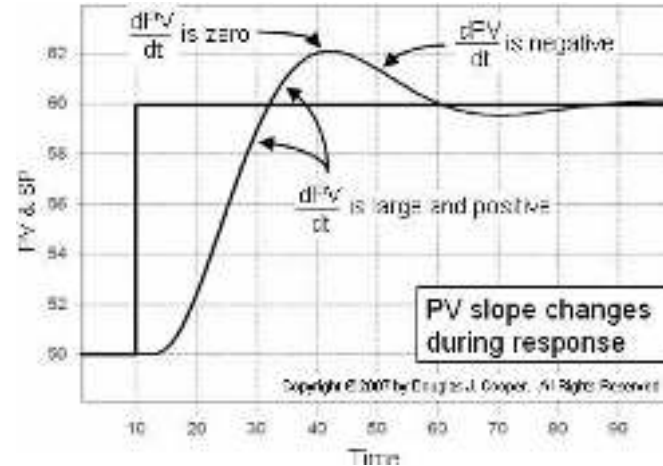
## Cons:

- Many ways of configuring, can be overkill
- Harder to predict behavior
- Derivative can be unstable, requires memory

## Algorithm:

$$CO = CO_{\text{bias}} + K_c \cdot e(t) + \frac{K_c}{T_i} \int e(t) dt + K_c \cdot T_d \frac{de(t)}{dt}$$

Could also have PD which removes the integral term



## Where:

- $CO$  = controller output signal
- $CO_{\text{bias}}$  = controller bias
- $e(t)$  = current controller error
- $SP$  = set point
- $PV$  = measured process variable
- $K_c$  = controller gain, tuned
- $T_i$  = reset time, tuned
- $T_d$  = derivative time, tuned

# When to use I or D?

## Problems with D

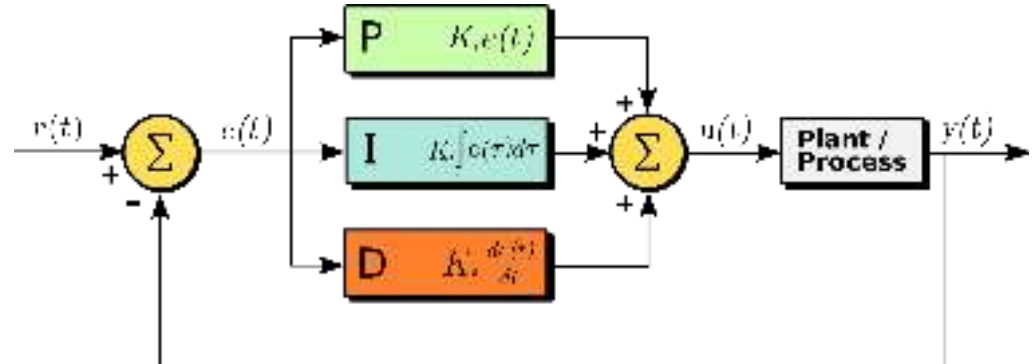
- Fast response to abrupt changes and disturbances (“kick”)
- High frequency noise entering in the system is highly amplified.

## Problems with I

- Slow response to abrupt changes and disturbances (“windup”)

## Which is ideal for:

- Thermostat?
- Cruise control?



# Smarter Industry Examples

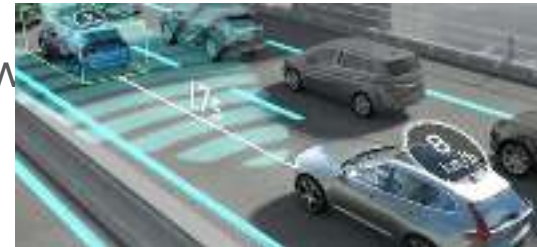
## Nest “Learning” Thermostat

- Source external information via wifi (local weather and grid load, user GPS)
- Learn from manual override (customer is always right)
- Learn users schedule (home vs away)
- Thermal modeling to improve temperature sensing



## “Adaptive” Cruise Control

- Add additional proximity sensors to determine distance to nearby vehicles
- Adjust speed to maintain cruise setpoint, but also stay w safe proximity of nearby vehicles
- Predict live traffic and road conditions





# Data Driven Controller Tuning

*If representative sensor data exists with ground truth of how the controller should have responded (supervised learning), then data driven techniques can be employed to improve control!*

## **Examples:**

- Tuning with parameter search (grid, random, evolutionary, gradient descent)
- Physical modeling (thermal, propulsion)
- Statistical modeling (bayesian, probabilistic, Hidden Markov)
- Non-linear machine learning (neural networks, ensembles, random forests)



Sensing

# Temperature Sensing

**Thermistor:** Exhibits a large, predictable, and precise change in resistance correlated to variations in temperature. As temperature increases results in resistance drops.

- **Exponential** rather than linear response, requires linearization (simpler than a lookup table)
- **Accuracy is high** from 0.05 to 1.5 °C and **fast response** time, **operating range** is -50 to 200 °C

**Thermocouple:** Consists of two wires of different metals connected at two points. The varying voltage between these two points reflects changes in temperature. As temperature goes up, the output voltage of the thermocouple rises.

- Thermocouples are **nonlinear** and often require a lookup table
- **Accuracy is low**, from 0.5 °C to 5 °C, **medium response** time, **widest operating range**, from -200 °C to 1750 °C.

**Semiconductor:** Found in side of ICs, typically two diodes with temperature sensitive voltage and current characteristics

- **Linear** response, so readings don't require post-processing
- **Lowest accuracy**, from 1 °C to 5 °C and **slowest response** (5s to a minute), and **Narrowest temperature** range, from -70 °C to 150 °C

**Infrared Imaging:** Infrared energy is emitted from an object as thermal radiation and is proportional to its temperature

- **Non-contact and long range** which is essential for some applications, but **100x more expensive**
- Non point source and therefore **less accurate** compared to above contact based sensors



# Temperature Sensing Engineering Problem

What can go wrong when a temperature sensor is packed into a “smart” consumer electronics product (like Nest Thermostat)?



# Autonomous Vehicles

Vehicles have been getting more “autonomous” since the 40s...



Windshield wipers 1944

A vintage advertisement for the Chrysler Windsor Dartline from 1958. The top half features a photograph of a light blue convertible car parked in front of a modern, two-story house with a woman sitting on a porch. Below the photo, the text reads: "It's all Chrysler and you'll like the price!". The advertisement includes several columns of small text describing the car's features, such as "The steering gear of its revolutionary Torsion Bar..." and "The 1958 Dartline is the most advanced car in the world...". A red rectangular box highlights a section on the right side of the ad that says "EXTRA! ANOTHER NEW auto-pilot" and "A Chrysler Engineering Exclusive that gives you speed...". At the bottom, it says "SEE AND DRIVE THE MIGHTY CHRYSLER DARTLINE".

Chrysler Windsor Dartline 1958

# Autonomous Vehicles Progress

**(1900s) Level 0:** Driver only: the human driver controls everything independently; *steering, throttle, brakes, etc*

**(1970s) Level 1:** Driver Assistance: Basic automatic control; *cruise control, automatic transmission*

**(2000s) Level 2:** Partial automation: Operator must monitor at all times. At least one fully automated system; *adaptive cruise control, auto braking or lane centering*

**(possible in 2010s, not legal) Level 3:** Conditional automation: The operator monitors the system and can intervene. Safety-critical functions can be automated

**(2020s fully legal?) Level 4:** High automation: There is no monitoring required for an entire trip. Not all trips supported, driver action could be necessary.

**(2030s?) Level 5:** Full automation: operator-free driving.



# Perception Sensors

**RADAR**



**Camera (360)**



**GPS**



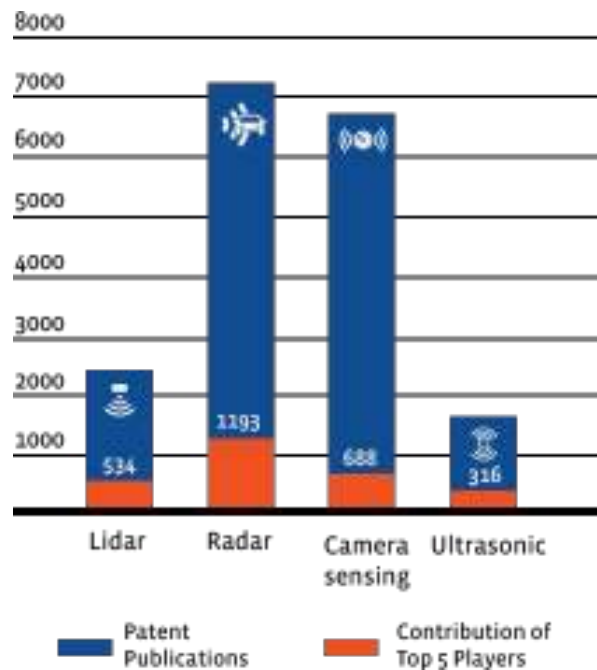
**LIDAR**



**ULTRASONIC**



# Perception Specs



## RADAR

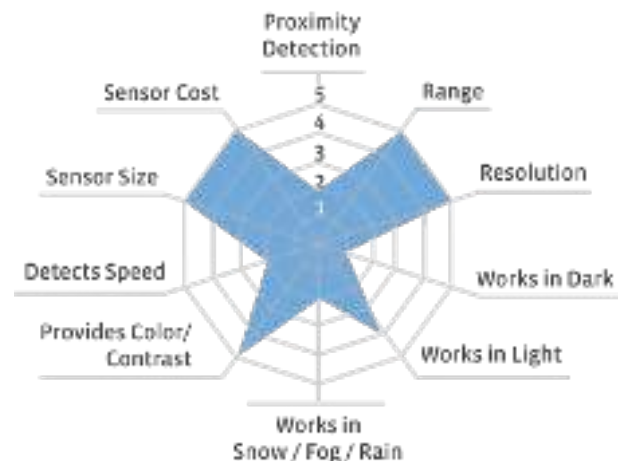


## LIDAR



## PASSIVE VISUAL

### Camera

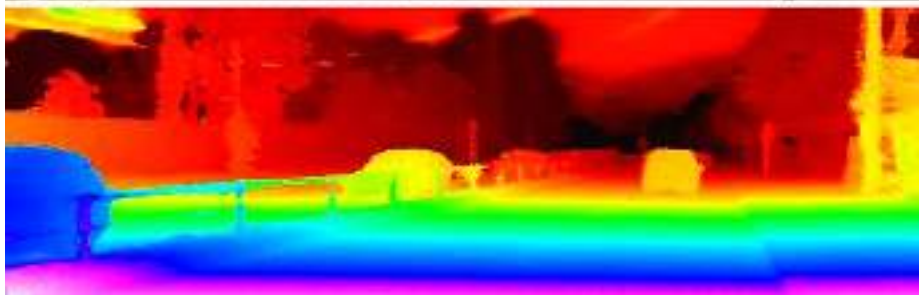


## ULTRASONIC

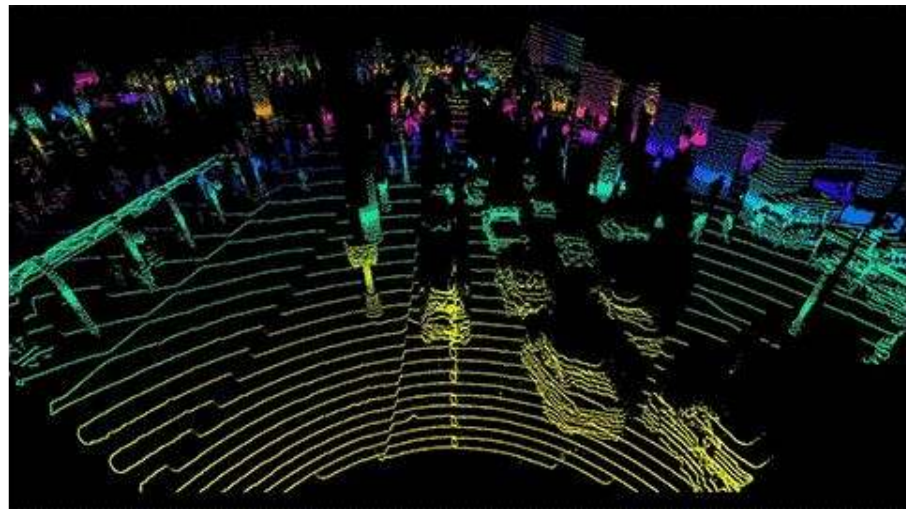
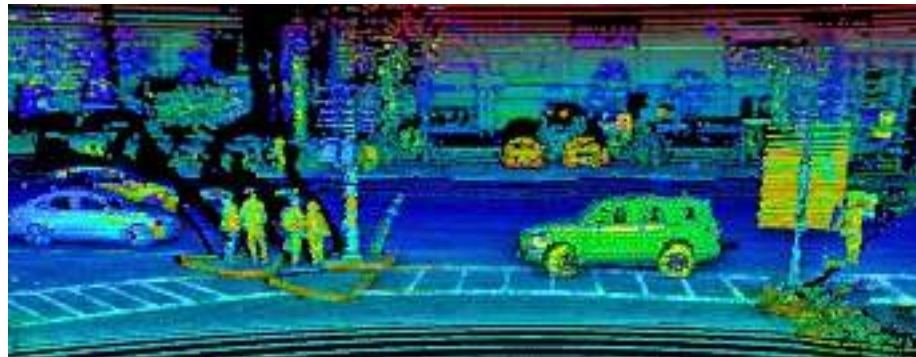


# Depth Perception Task

## Stereo Cameras

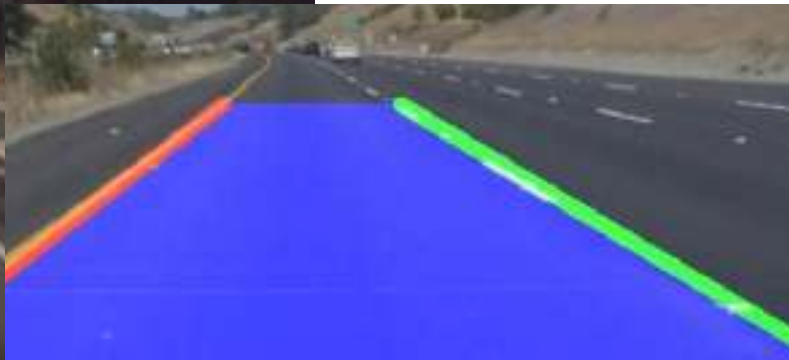
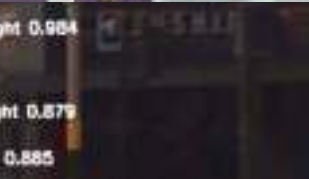
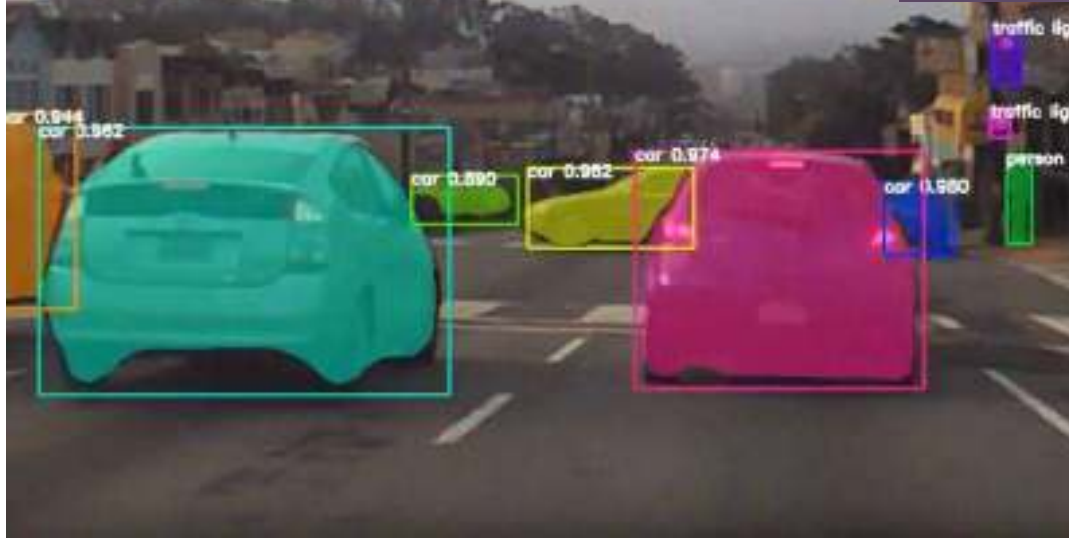


## Radar / Lidar

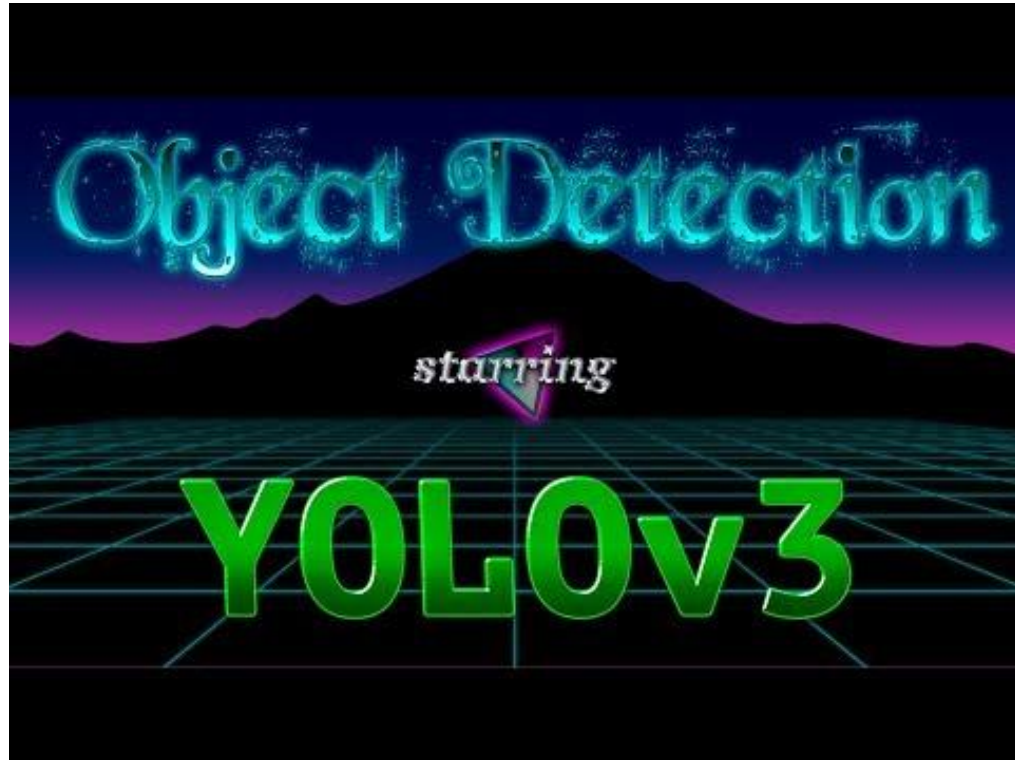


# Object Detection Task

Typically cameras

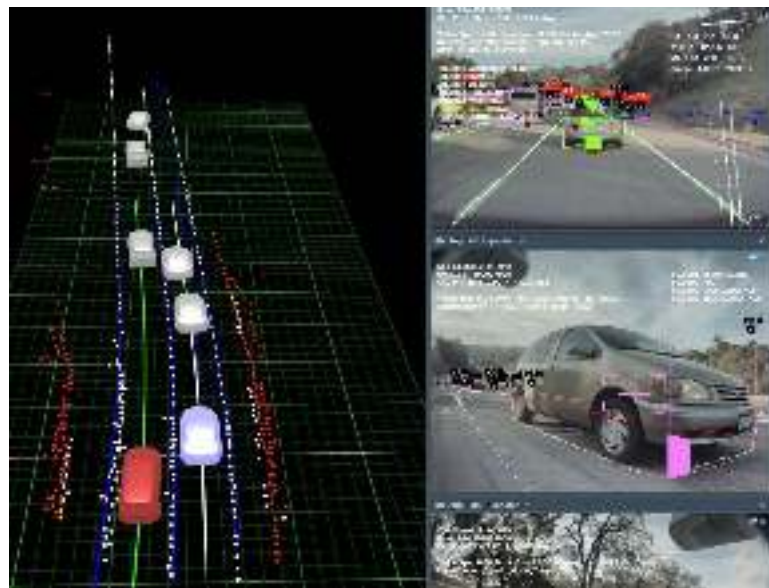
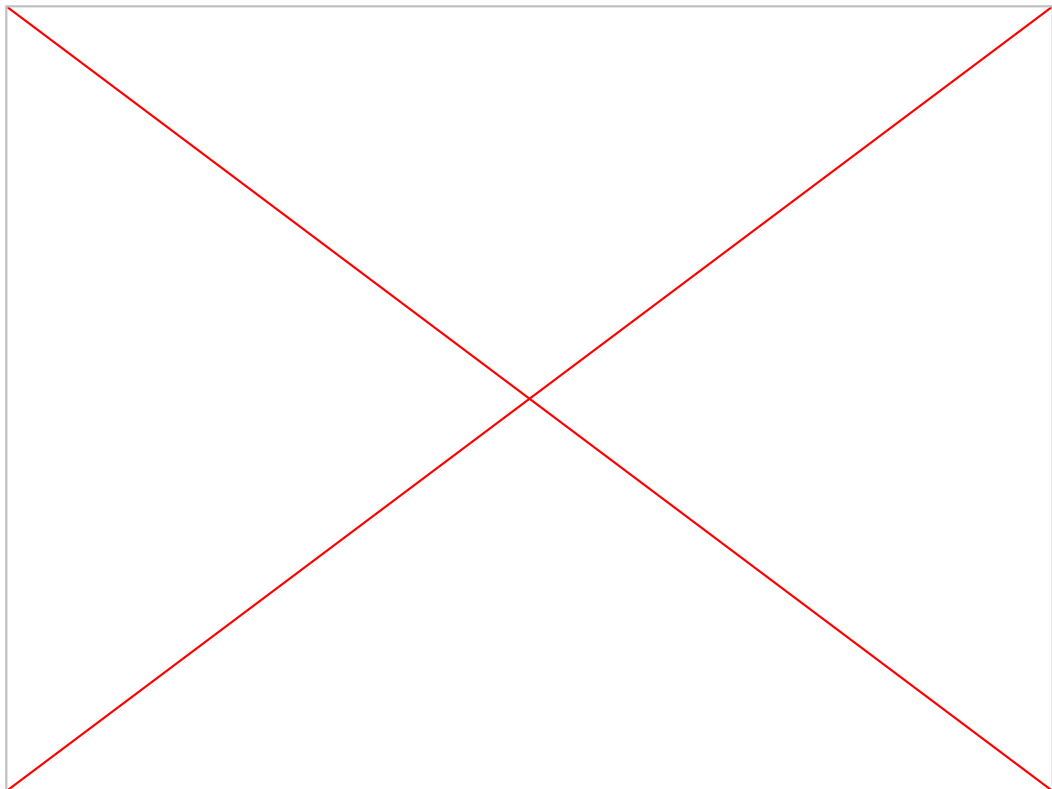


# Deep Learning for Camera Object Detection



# Tesla Autopilot

## Sensor Fusion



# Model X Falcon Wing Door Sensors

## Sensors

- Ultrasonic
- Capacitive
- Inductive

## Features

- Wall / person / obstruction avoidance
- Adaptive path planning algorithm
- Safety Overrides



# Carpacio: Repurposing Capacitive Sensors to Distinguish Driver and Passenger Touches on In-Vehicle Screens

Edward Jay Wang<sup>1,\*</sup>, Jake Garrison<sup>1,\*</sup>, Eric Whitmire<sup>2</sup>, Mayank Goel<sup>3</sup>, Shwetak Patel<sup>1,2</sup>

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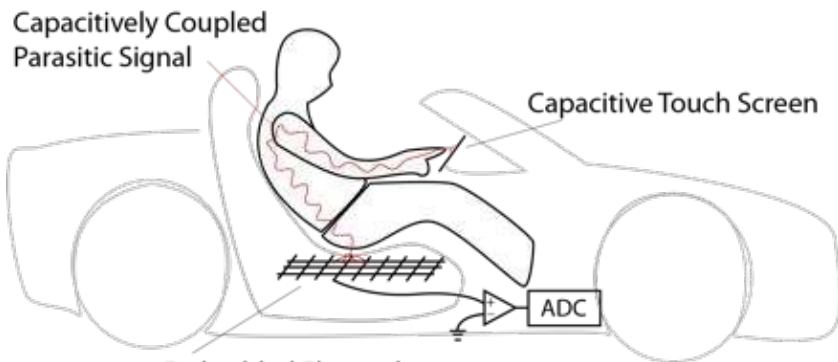
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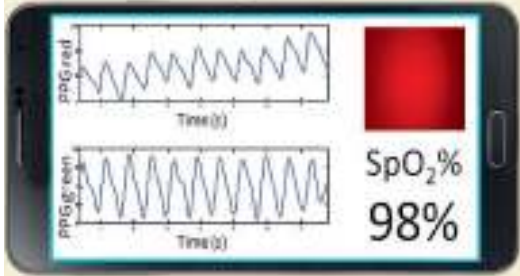
mayankgoel@cmu.edu



Embedded Electrode

Wire meshes embedded in car seats (such as the heated car seats) acts as electrodes to measure the coupled signal

# Mobile Health Sensing





# Processing

# Processor Hardware

GPU



Microprocessors / FPGA



Atmel AVR



AVR



ATX Mega



ATmega 328P



PIC 18F877A



8051



Arduino



ARM

DSP



CPU



TPU



ASIC

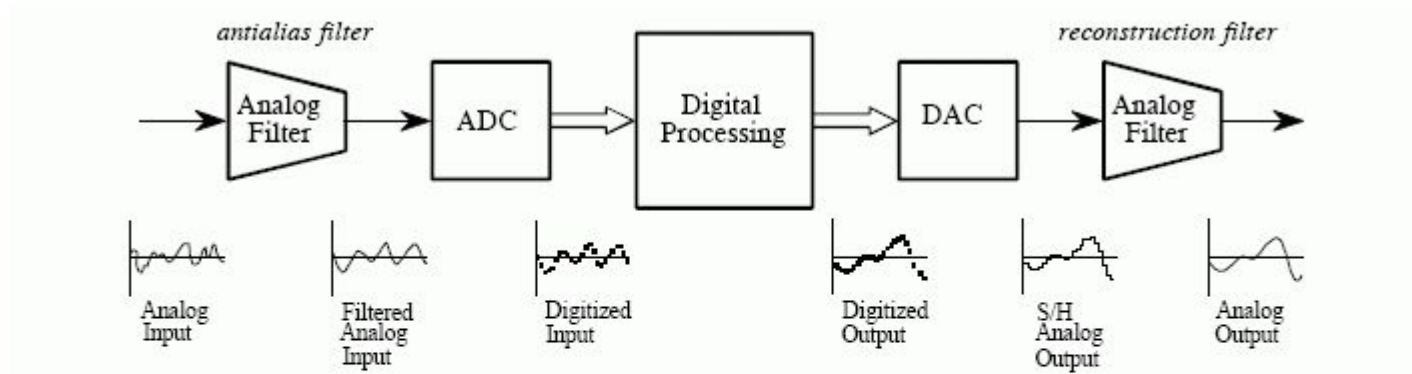


Millimeter scale



# Signal Processing

- Input analog signal sensing: *microphone, antenna, transducer*
- Analog processing: *amplification, filtering, mixing*
- ADC (analog to digital converter)
- Digital signal processing, DSP: *resampling, filtering frequency and time modulation, compression, detection inference*
- DAC (digital to analog converter)
- Output analog signal: *speaker, encoded file, packet, output instruction*



# Signal Processing is Everywhere

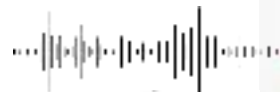
*Recording*



*DSP FX*



*Understanding*



Hey Google  
who is Kanye West?



*Rendering*



*Compression*



*Storage*



*Transmission*



*Playback*



# Questions / Discussion

- Signal Processing
  - Analog circuits
  - Digital signal processing + Machine learning
  - Hardware processors
- Control Algorithms
- Smart Home
  - Thermostats
  - Voice assistants
- Mobile Health Sensing
- Automotive
  - Electric vehicles
  - Autonomous vehicles
- Industry
  - Tech Startups (puppy.ai, Haiku Deck, Cryptocurrency, getting acquired)
  - Tech companies (Google, Tesla, Nest, General motors)
  - Interviewing tips

# Thanks!

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# Sources

<https://controlguru.com/the-components-of-a-control-loop/>

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