

# COMP417

## Introduction to Robotics and Intelligent Systems

### Lecture 5: PID Control

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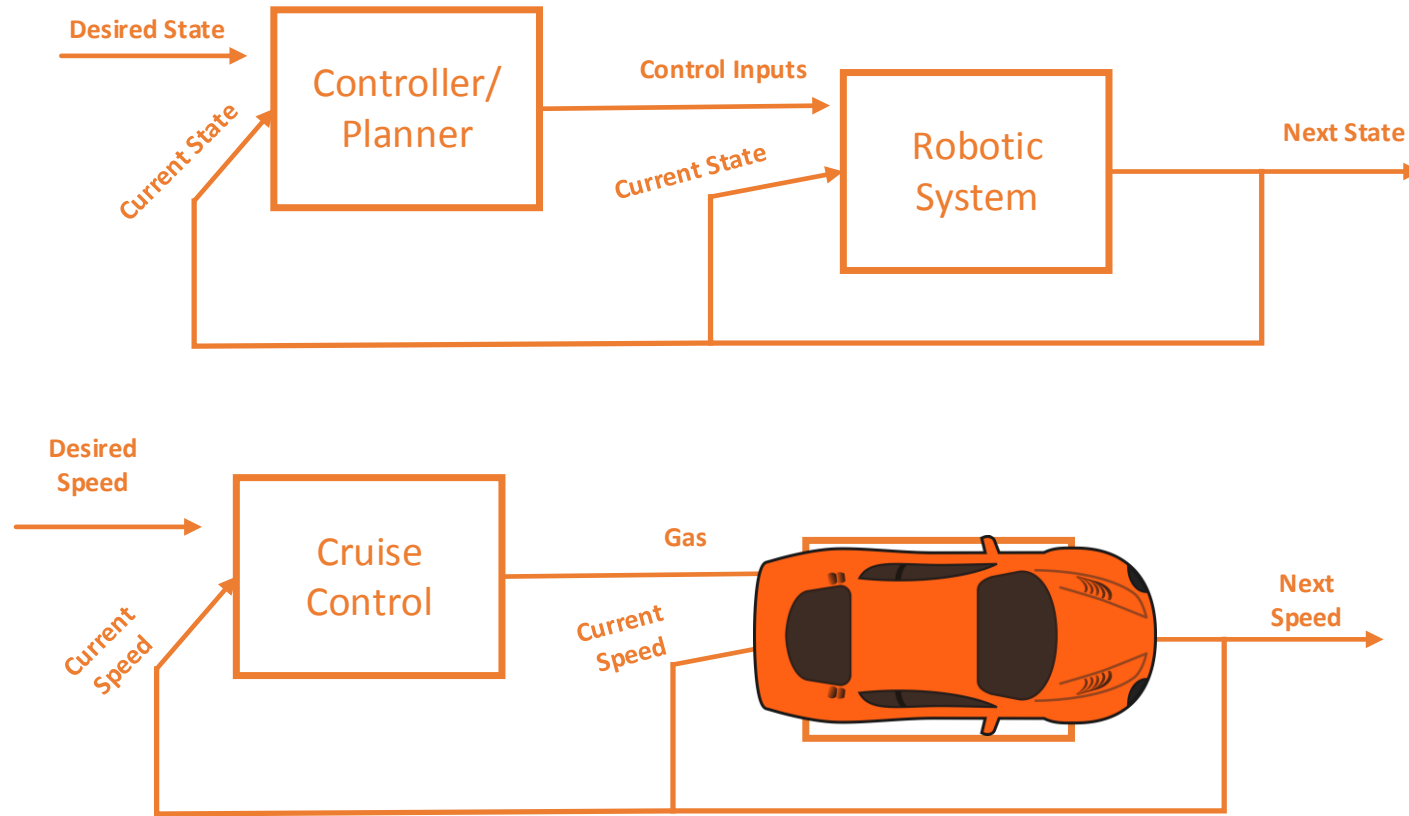
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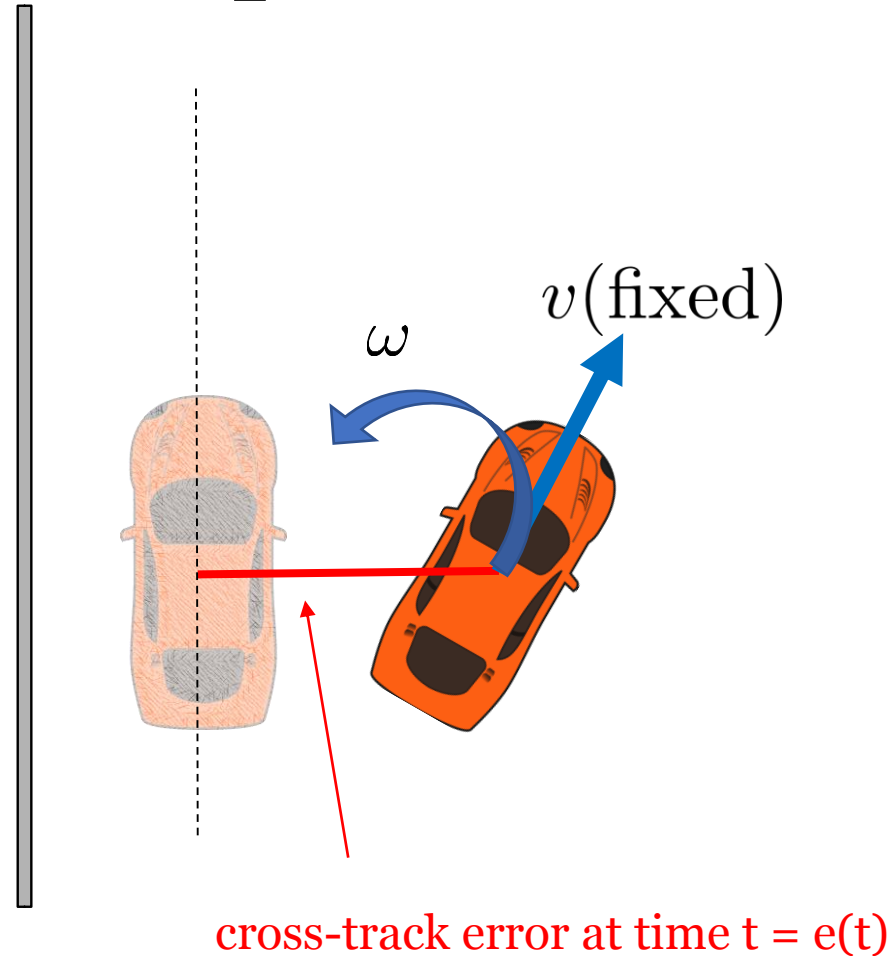
# Feedback Control



Main question: what are the controls that will take the system from state A to B?

# Example: wall/line following at fixed speed

You have to control the angular velocity  $\omega$



# Why bother with wall/line following?

- Because it enables arbitrary path following where the line is the local tangent of the (curvy) path

# Idea 1: bang-bang control

$$\omega = \begin{cases} \omega_{\max} & \text{if } \text{CTE} > 0 \\ -\omega_{\max} & \text{if } \text{CTE} < 0 \\ 0 & \end{cases}$$

What's wrong with this?

# Idea 2: proportional (P-)control

$$\omega = K_p e(t)$$

Will the car reach the target line?

Will the car overshoot the target line?

Is the asymptotic (steady-state) error zero?

A line of orange cars is shown from a top-down perspective, following a curved path. A vertical dashed line represents the target line. The cars are positioned to the left of this line, indicating a steady-state error. The path they follow curves away from the target line.

# Idea 2: proportional (P-)control

$$\omega = K_p e(t)$$

Will the car reach the target line? YES

Will the car overshoot the target line? YES

Is the asymptotic (steady-state) error zero? NO

# Addressing the oscillation problem

- Need to reduce turning rate **well before** the line is approached
- Idea: have a small proportional gain  $K_p$   
Problem: that means the car doesn't turn very much
- Idea: need to **predict the error** in the near future  
This is good, as long as the error does not oscillate at a very high frequency



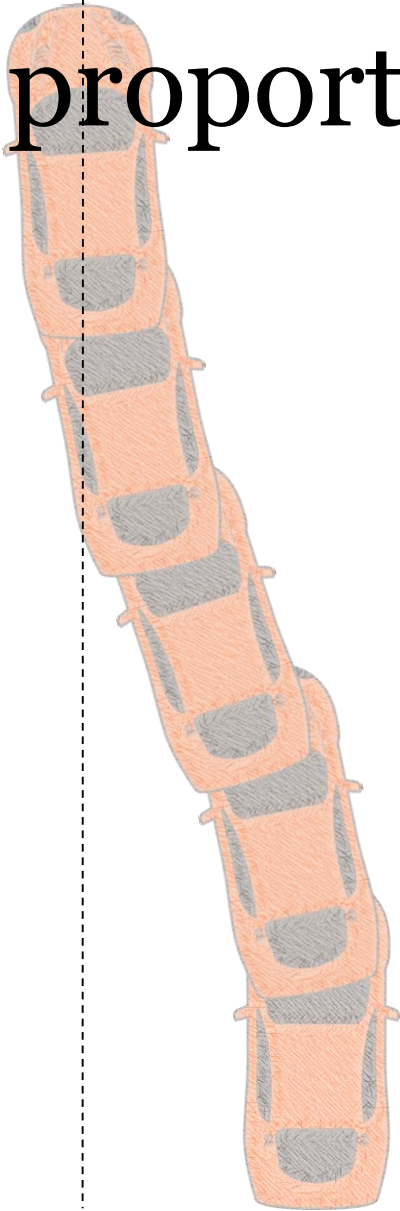
# Idea 3: proportional-derivative (PD-)control

$$\omega = K_p e(t) + K_d \dot{e}(t)$$

How do we set the gains?

What if there are systematic errors/biases?

What if the error estimate is very noisy?



# Handling systematic biases: the integral term

- Examples of systematic biases:
  - wheels are misaligned
  - car is much heavier on one side
- Add integral of the error from the beginning of time:  $\int_{\tau=0}^{\tau=t} e(\tau) d\tau$
- Can the PI-controller have nonzero error asymptotically (in steady-state)?
  - NO. In steady state both the control  $\omega_{\infty}$  and the error  $e_{\infty}$  must be constant. If the asymptotic error is nonzero then the control is not constant:  $\omega_{\infty} = K_p e_{\infty} + K_i e_{\infty} t$

# Potential problem: integrator windup

- What happens if the control variable reaches the actuator's limits?
- I.e. the car can't turn as fast as the controller commands it.
- Actuator may remain at its limit for a long time while the controller modifies its commands
- Error increases, integral term winds up while controller goes back to issuing commands in the feasible region.

# Potential problem: integrator windup

- Heuristic fixes:
  - Limit integral error values
  - Stop integral error while the commands are in the non feasible region
  - Reduce gain of integral error term

# PID controller

$$\omega(t) = K_p e(t) + K_d \dot{e}(t) + K_i \int_{\tau=0}^{\tau=t} e(\tau) d\tau$$

Perhaps the most widely used controller in industry and robotics.  
Perhaps the easiest to code.

You will also see it as:

$$\omega(t) = K_p [e(t) + T_d \dot{e}(t) + \frac{1}{T_i} \int_{\tau=0}^{\tau=t} e(\tau) d\tau]$$

# Tips: how to implement PID

- Assume time is discrete
- Identify your error function  $e(t) = \text{current\_state}(t) - \text{target\_state}(t)$
- Is the measurement of the state reliable?
- If the measurement of the current state is very noisy you might want to smooth/filter it, using:

- **Moving average filter** with uniform weights

$$\hat{x}_t = \frac{x_t + x_{t-1} + \dots + x_{t-k+1}}{k} = \hat{x}_{t-1} + \frac{x_t - x_{t-k}}{k}$$

Potential problem: the larger the window of the filter the slower it is going to register changes.

- **Exponential filter**

$$\hat{x}_t = \alpha \hat{x}_{t-1} + (1 - \alpha)x_t, \quad \alpha \in [0, 1]$$

Potential problem: the closer  $\alpha$  is to 1 the slower it is going to register changes.

# Tips: how to implement PID

- Approximate the integral of error by a sum
- Approximate the derivative of error by:
  - Finite differences  $\dot{e}(t_k) \approx \frac{e(t_k) - e(t_{k-1})}{\delta t}$
  - Filtered finite differences, e.g.  $\dot{e}(t_k) \approx \alpha \dot{e}(t_{k-1}) + (1 - \alpha) \frac{e(t_k) - e(t_{k-1})}{\delta t}$
- Limit the computed controls
- Limit or stop the integral term when detecting large errors and windup

# Tips: how to tune the PID

- Manually:
  - First, use only the proportional term. Set the other gains to zero.
  - When you see oscillations slowly add derivative term
    - Increasing  $K_d$  increases the duration in which linear error prediction is assumed to be valid
  - Add a small integral gain



# Tips: how to tune the PID

- Ziegler-Nichols heuristic:
  - First, use only the proportional term. Set the other gains to zero.
  - When you see consistent oscillations, record the proportional gain  $K_u$  and the oscillation period  $T_u$

Ziegler–Nichols method <sup>[1]</sup>			
Control Type	$K_p$	$T_i$	$T_d$
$P$	$0.5K_u$	-	-
$PI$	$0.45K_u$	$T_u/1.2$	-
$PD$	$0.8K_u$	-	$T_u/8$
classic PID <sup>[2]</sup>	$0.6K_u$	$T_u/2$	$T_u/8$

# Tips: how to tune the PID

- After manual or Z-N tweaking you might want to use coordinate ascent to search for a better set of parameters automatically:

See Sebastian Thrun's online class "AI for robotics" on Udacity for more details on this. He calls the algorithm Twiddle and it is in Lesson 5.

```
# Choose an initialization parameter vector
p = [0, 0, 0] # [K_p, K_i, K_d]
# Define potential changes
dp = [1, 1, 1]
# Calculate the error
best_err = run_controller(p)

threshold = 0.001

while sum(dp) > threshold:
    for i in range(len(p)):
        p[i] += dp[i]
        err = run_controller(p)

        if err < best_err: # There was some improvement
            best_err = err
            dp[i] *= 1.1
        else: # There was no improvement
            p[i] -= 2*dp[i] # Go into the other direction
            err = run_controller(p)

            if err < best_err: # There was an improvement
                best_err = err
                dp[i] *= 1.05
            else # There was no improvement
                p[i] += dp[i]
                # As there was no improvement, the step size in either
                # direction, the step size might simply be too big.
                dp[i] *= 0.95
```

# When is PID insufficient?

- Systems with large time delays
- Controllers that require completion time guarantees
  - E.g. the system must reach target state within 2 secs
- Systems with high-frequency oscillations
- High-frequency variations on the target state

# Example applications: self-driving cars



# Cascading PID

- Sometimes we have multiple error sources (e.g. multiple sensors) and one actuator to control.
- We can use a master PID loop that sets the setpoint for the slave PID loop. Master (outer loop) runs at low rate, while slave (inner loop) runs at higher rate.
- One way of getting hierarchical control behavior.