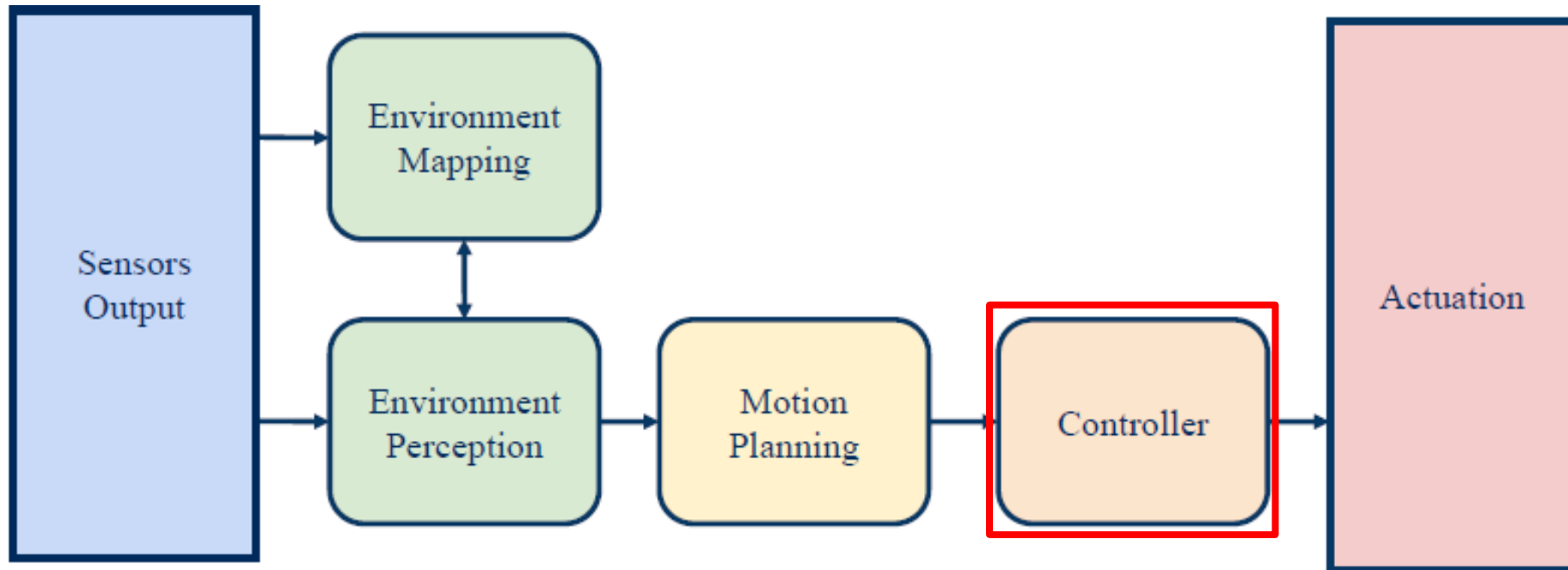


# L6 Control

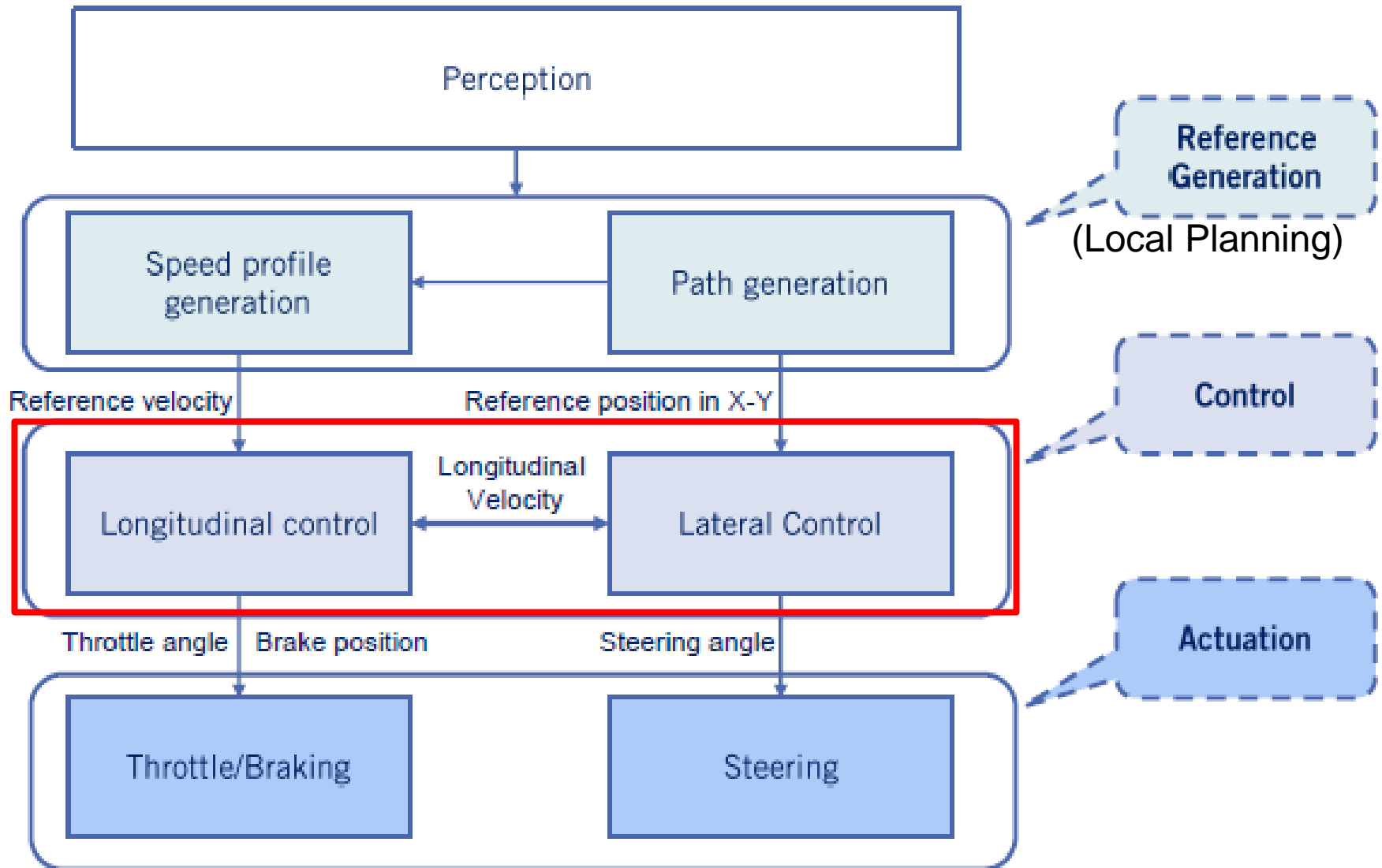
Z. Gu, 2021

# Controller Design

- We need to design a controller to follow the trajectory output from motion planning.
  - Many control algorithms. We mainly discuss PID and MPC, the two most widely-used control algorithms for AVs.
  - We only give the basic intuition and avoid mathematical details.

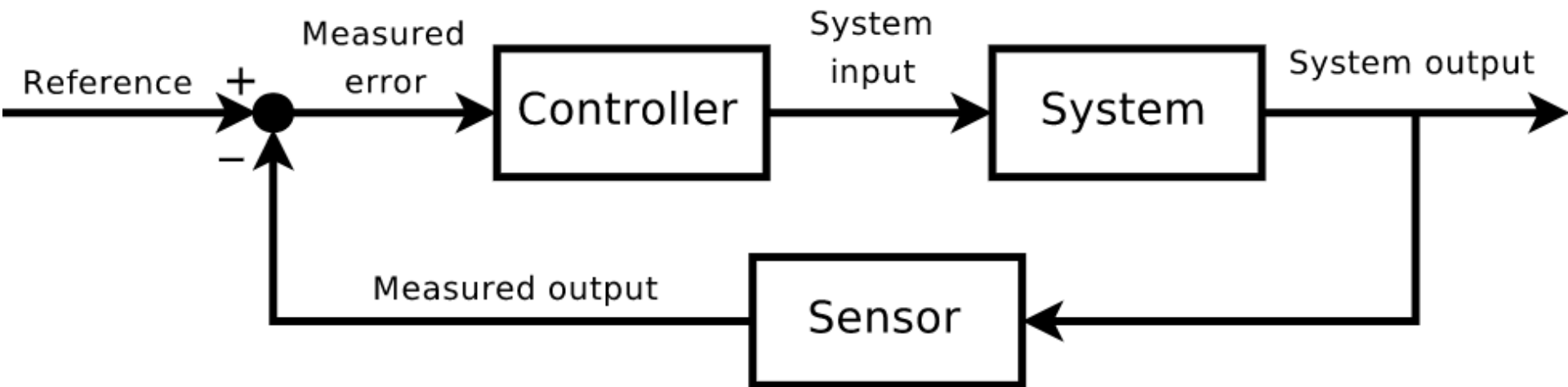


# Vehicle Control Architecture



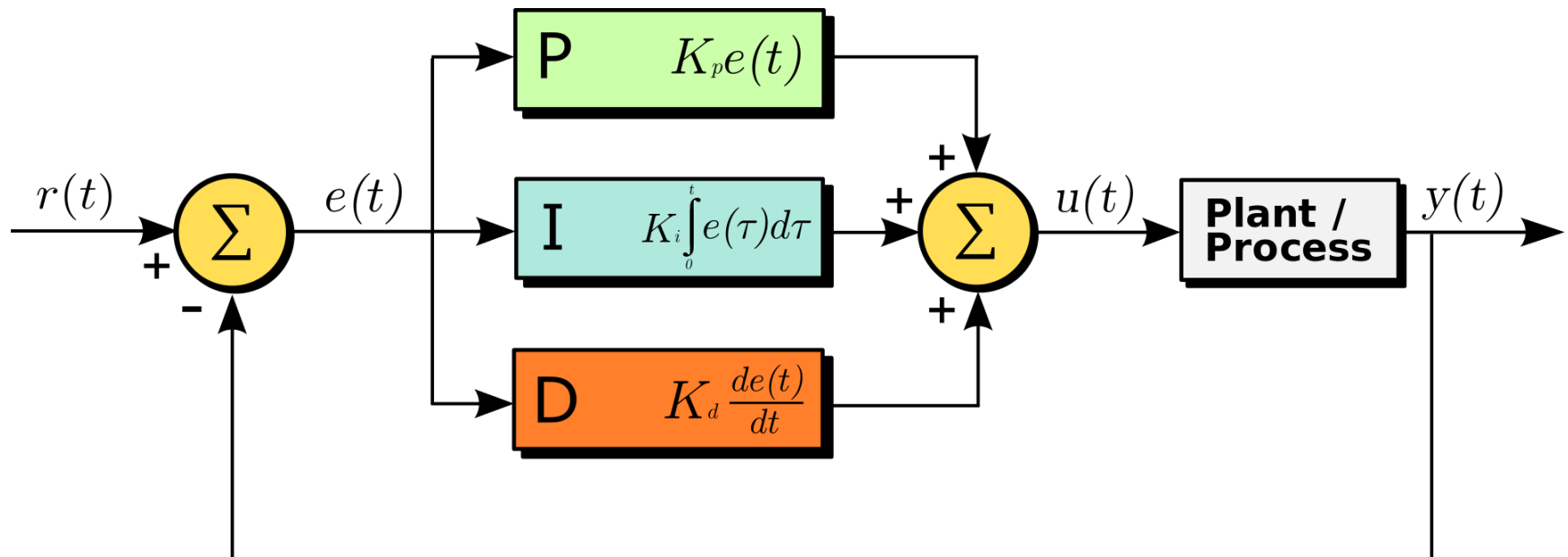
# The Feedback Control Problem

- Given a system and a reference signal, find a control law such that the closed loop system is stable and follows the reference signal.



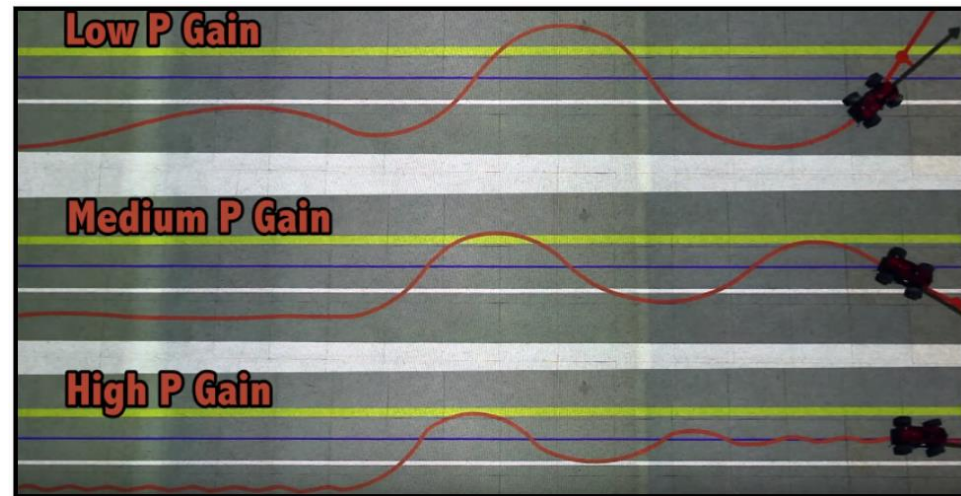
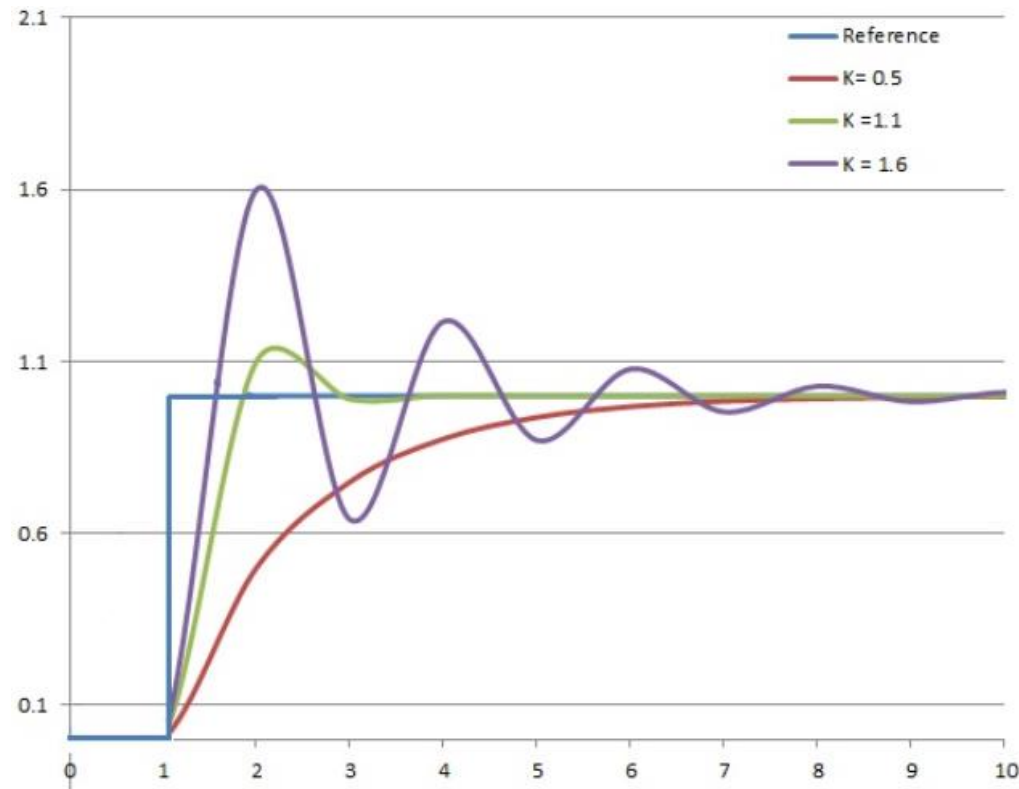
# PID Control

- Tracking Error:  $e(t) = r(t) - y(t)$
- Control input:  $u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \dot{e}(t)$



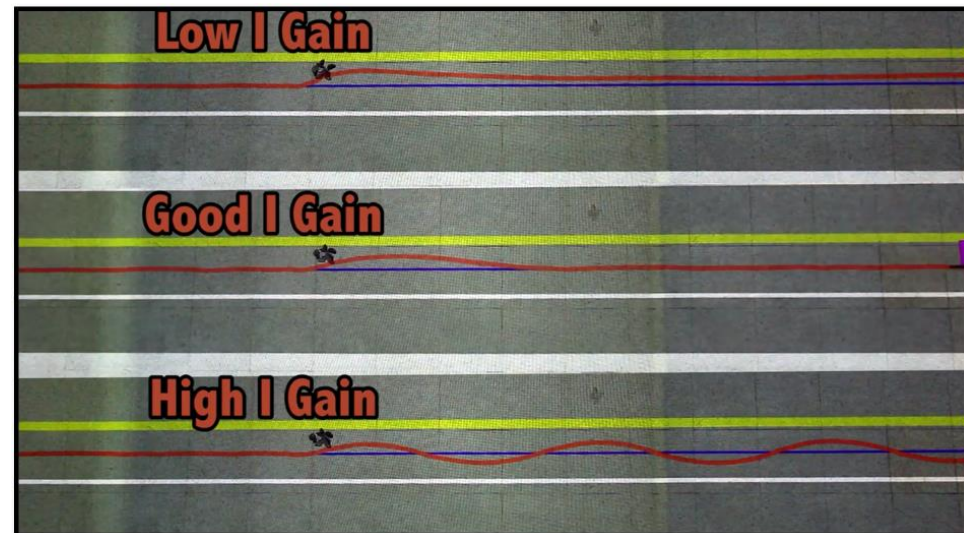
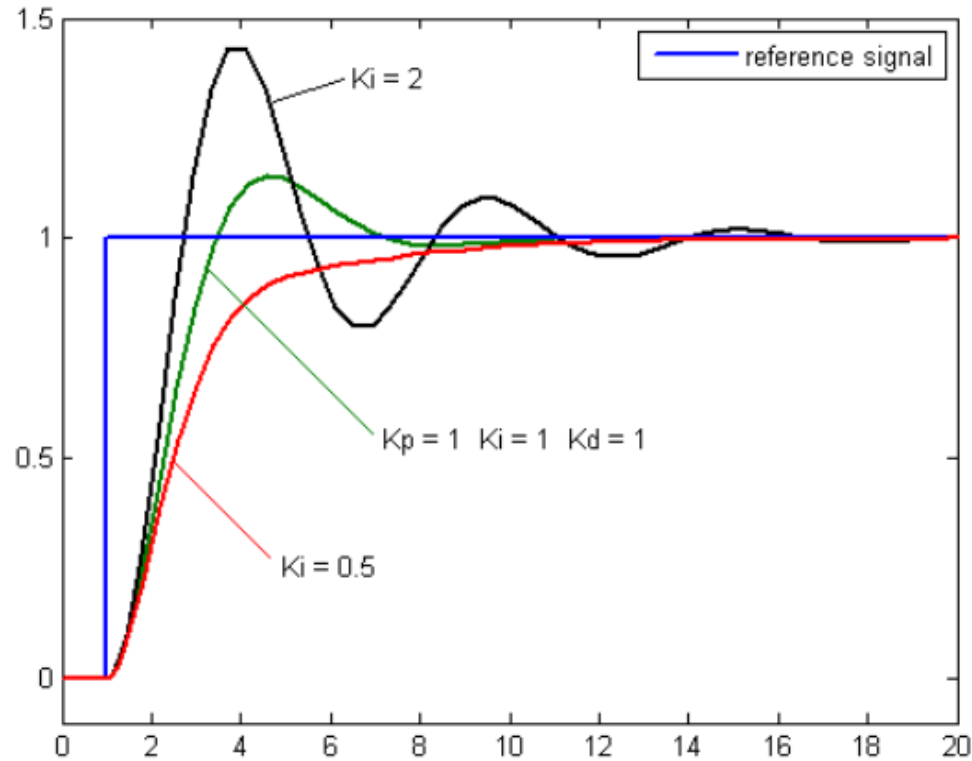
# Proportional Term $K_p$

- Increasing  $K_p$  causes:
  - Faster response
  - Bigger overshoot, oscillations
    - System may become unstable
  - Smaller but non-zero steady state error



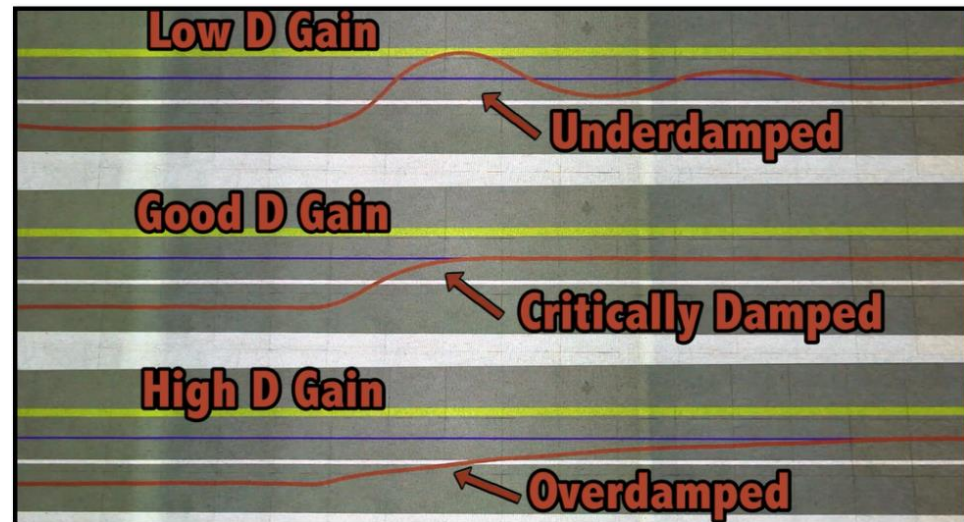
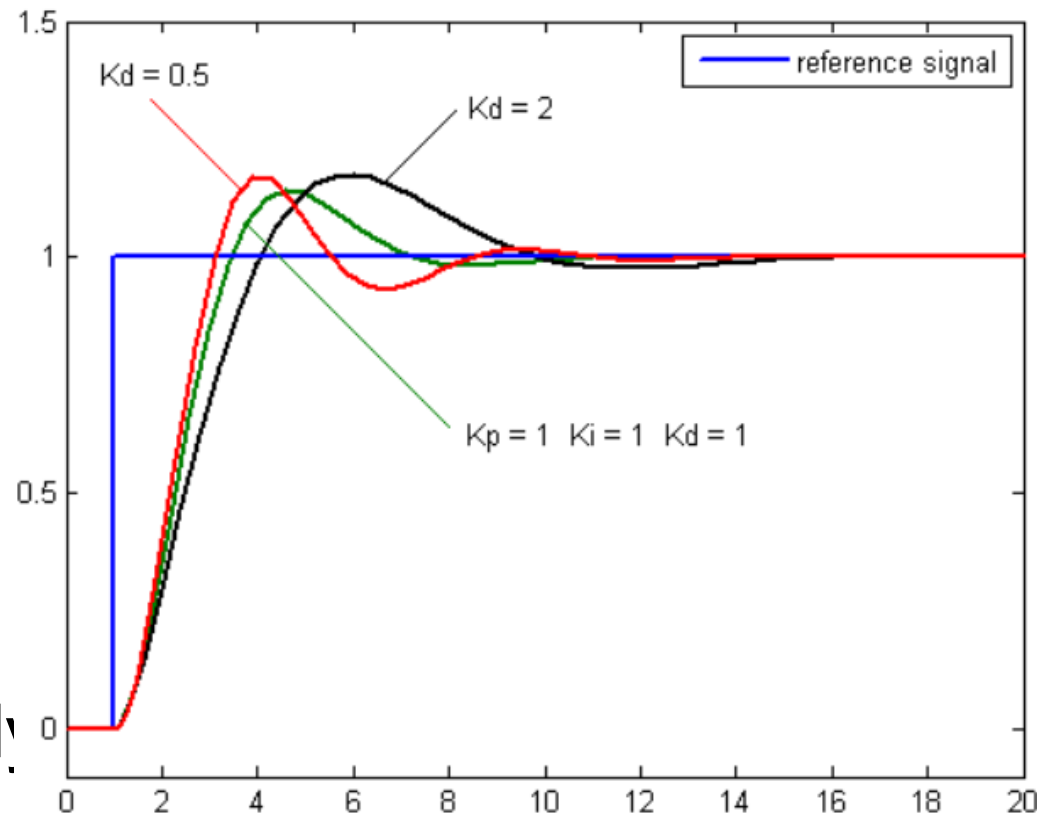
# Integral Term $K_i$

- $K_i$  takes into account history of tracking error, and eliminates steady state error
- Increasing  $K_i$  causes:
  - Increases overshoot
  - More robust to disturbances



# Derivative Term $K_d$

- Increasing  $K_d$  causes:
  - Reduced overshoot
  - Faster response
  - Little effect on steady state
  - More sensitive to measurement noise



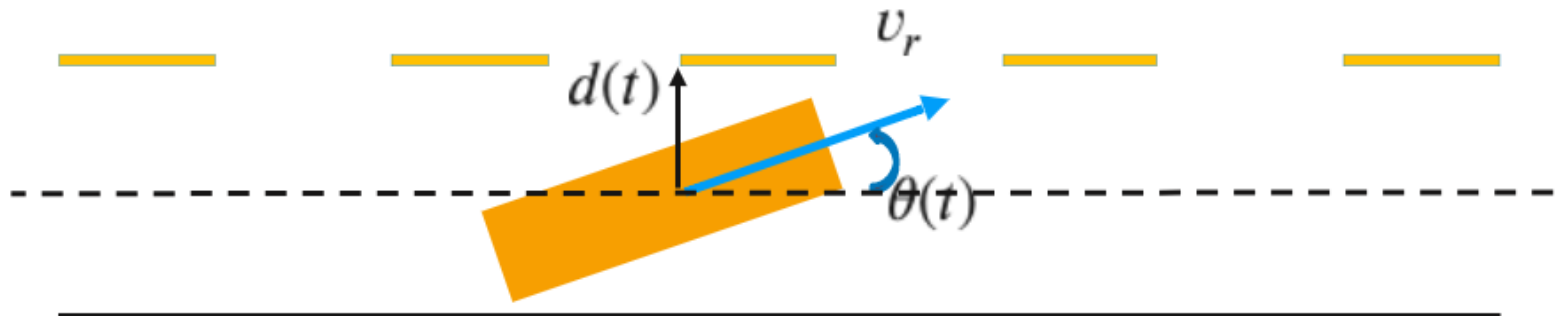
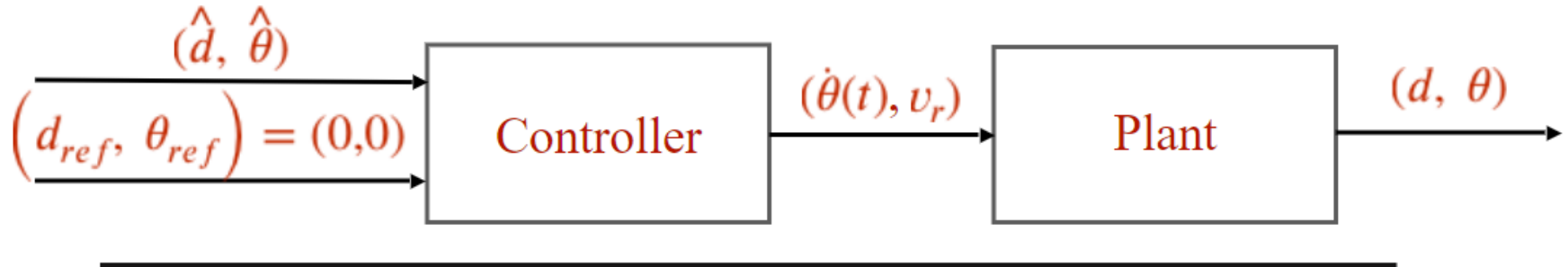


# Summary of Effects of PID Gains

Closed-Loop Response	Rise Time	Overshoot	Settling Time	Steady State Error
Increase $K_p$	Decrease	Increase	Small change	Decrease
Increase $K_i$	Decrease	Increase	Increase	Eliminate
Increase $K_d$	Small change	Decrease	Decrease	Small change

# Example: Vehicle Lateral Control

- State  $(d, \theta)$ 
  - $d$ : distance to center of lane;  $\theta$ : heading angle.
- Reference trajectory:  $(d_{ref}, \theta_{ref}) = (0, 0)$ 
  - The vehicle travels straight ahead at center of lane.
- Vehicle has constant speed  $v_r$ , so the only control input is  $u(t) = \dot{\theta}(t)$ , the angular velocity.
- Assume perfect sensor state estimation:  $(\hat{d}, \hat{\theta}) = (d, \theta)$



# System and Controller Modeling

- Linear system dynamics:

- $\begin{bmatrix} \dot{d}(t) \\ \dot{\theta}(t) \end{bmatrix} = \begin{bmatrix} 0 & v_r \\ 0 & 0 \end{bmatrix} \begin{bmatrix} d(t) \\ \theta(t) \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u(t)$

- $\dot{d}(t) = v_r \sin \theta(t) \approx v_r \theta(t)$  assuming  $\theta(t)$  is small. This is a linearized kinematic model.

- P Controller:

- $u(t) = \begin{bmatrix} K_d & K_\theta \end{bmatrix} \begin{bmatrix} d(t) \\ \theta(t) \end{bmatrix}$

- Closed-loop dynamics is obtained by plugging  $u(t)$  into system dynamics:

- $\begin{bmatrix} \dot{d}(t) \\ \dot{\theta}(t) \end{bmatrix} = \begin{bmatrix} 0 & v_r \\ K_d & K_\theta \end{bmatrix} \begin{bmatrix} d(t) \\ \theta(t) \end{bmatrix}$

- (Please note symbol – above is NOT a minus sign!)

# System and Controller Modeling

- Ref trajectory:  $\begin{bmatrix} d_{ref} \\ \theta_{ref} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$

- Error signal:

$$- \begin{bmatrix} e_d(t) \\ e_\theta(t) \end{bmatrix} = \begin{bmatrix} d_{ref} \\ \theta_{ref} \end{bmatrix} - \begin{bmatrix} d(t) \\ \theta(t) \end{bmatrix} = - \begin{bmatrix} d(t) \\ \theta(t) \end{bmatrix}$$

- Error dynamics:

$$- \begin{bmatrix} \dot{e}_d(t) \\ \dot{e}_\theta(t) \end{bmatrix} = - \begin{bmatrix} \dot{d}(t) \\ \dot{\theta}(t) \end{bmatrix} = \begin{bmatrix} 0 & -v_r \\ -K_d & -K_\theta \end{bmatrix} \begin{bmatrix} d(t) \\ \theta(t) \end{bmatrix}$$

- We need to design  $K_d, K_\theta$  to drive  $\begin{bmatrix} e_d(t) \\ e_\theta(t) \end{bmatrix}$  to  $\begin{bmatrix} 0 \\ 0 \end{bmatrix}$

# Control Design with Pole Placement (not covered in this course)

- Closed-loop poles:

- $0 = \det(\lambda I - \begin{bmatrix} 0 & -v_r \\ -K_d & -K_\theta \end{bmatrix}) = \lambda^2 + K_\theta \lambda - v_r K_d$

- Solution  $\lambda_{1,2} = -\frac{K_\theta}{2} \pm \frac{1}{2} \sqrt{K_\theta^2 + 4v_r K_d}$

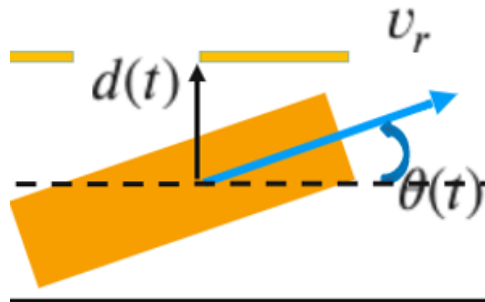
- Critically-damped dynamics (repeated real roots):

- $\sqrt{K_\theta^2 + 4v_r K_d} = 0 \Rightarrow K_d = -\frac{K_\theta^2}{4v_r}$

- $K_\theta$  chosen empirically

# Control Design cont'd

- Linear systems dynamics relies on the small angle approximation  $\sin \theta(t) \approx \theta(t)$ . To keep it valid, i.e.,  $|\theta(t)| < \theta_{th}, \forall d(t)$ ,
- Closed-loop dynamics  $\dot{\theta}(t) = K_d d(t) + K_\theta \theta(t)$ 
  - Change to  $\dot{\theta}(t) = K_d \text{sat}(d(t), d_{th}) + K_\theta \theta(t)$
  - where:  $\text{sat}(d(t), d_{th}) = \begin{cases} -d_{th} & d(t) < -d_{th} \\ d(t) & d(t) \in [-d_{th}, d_{th}] \\ d_{th} & d(t) > d_{th} \end{cases}$
- For example: to have  $\theta_{th} = \frac{\pi}{6}$ , set  $d_{th} = \left| \frac{K_\theta \theta_{th}}{K_d} \right|$ 
  - Even if the vehicle is very far from center of lane, do not change heading angle  $\theta(t)$  too fast (keep  $\dot{\theta}(t)$  small).
  - (I think it is a rule of thumb, not a hard guarantee.)

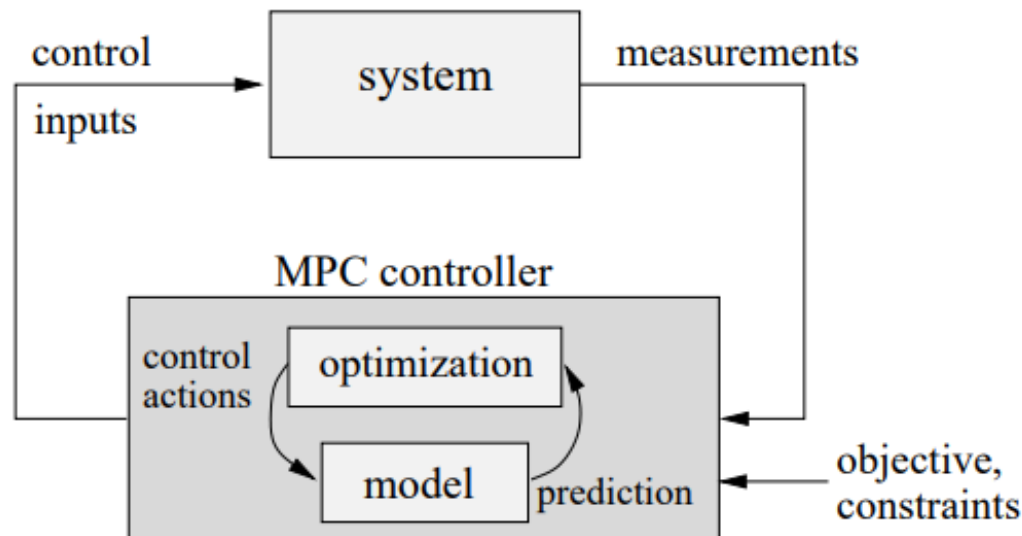


# Simplifying Assumptions We Made

- We did not consider:
  - Estimation uncertainty due to measurement noise
    - We assume perfect state estimation  $(\hat{d}, \hat{\theta}) = (d, \theta)$
  - Estimation latency:
    - Time from measurements  $(d, \theta)$  to state estimation  $(\hat{d}, \hat{\theta})$  availability to the controller
  - Constraints (e.g., actuator limits)
    - We may need to impose a maximum curvature radius to simulate a real car.
  - Discrete time (multi-rate), non-uniform sampling:
    - Our controller is continuous time, but the actual implementation runs in discrete time.
    - Sampling rate of the estimator (slower) may be different than that of actuation (faster), or may be variable.

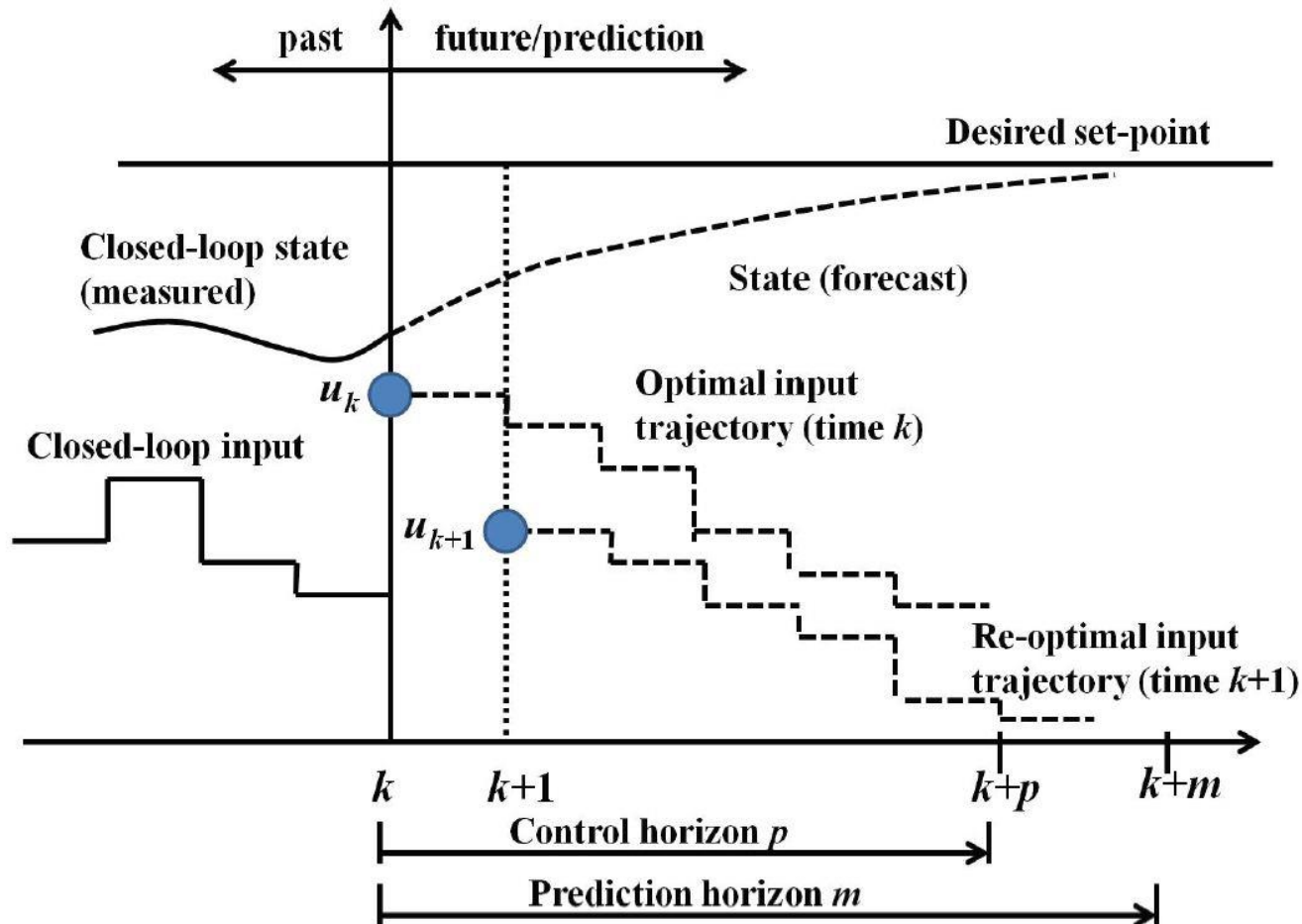
# MPC (Model-Predictive Control)

- Also called Receding Horizon Control
- Choose prediction horizon  $m$  and control horizon  $p$
- At each time step  $k$ :
  - Set initial state to predicted state  $x[k]$
  - Solve a constrained optimization problem over lookahead window  $[k, k + m]$ , to get a sequence of control inputs  $u$ , while in the time interval  $[k - 1, k]$
  - Apply 1<sup>st</sup> control command  $u[k]$  at time step  $k$



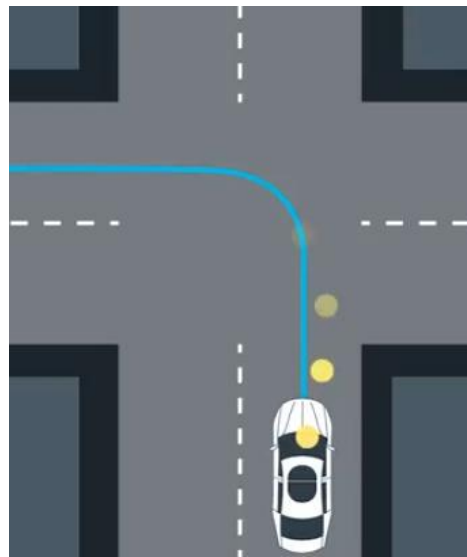


# MPC Illustration

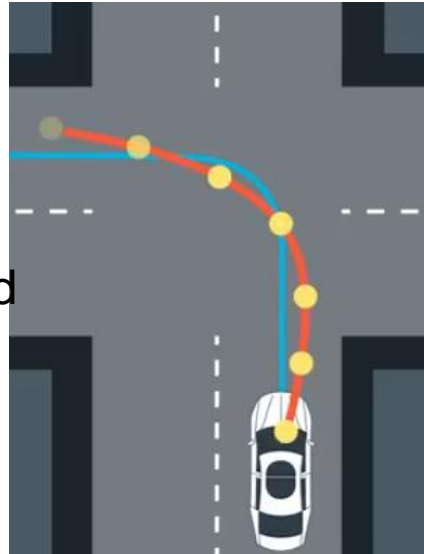
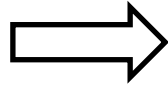


- Control horizon  $p$  and prediction horizon  $m$  may be different, but often the same (denoted as lookahead horizon  $T$  in next slides).
- “input trajectory” refers to computed control inputs  $U = \{u_k, \dots, u_{k+p-1}\}$ , not state trajectory.

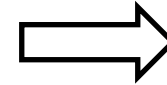
# MPC Illustration Con't



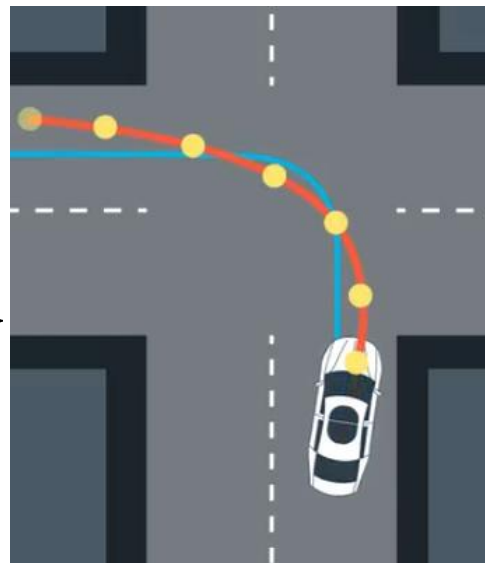
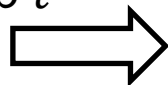
Solve for opt  
control inputs  
 $U =$   
 $\{u_t, \dots, u_{t+T-1}\}$   
within lookahead  
horizon  $T$  to  
track the blue  
desired traj



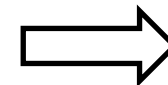
Execute  
control  
input  $u_t$   
at 1<sup>st</sup>  
timestep



Replan a  
new set of  
control  
inputs  $U =$   
 $\{u_t, \dots, u_{t+T-1}\}$   
at next time  
step  $t$



Execute  
control  
input  $u_t$  at  
1<sup>st</sup>  
timestep



...

# MPC Illustration Con't

- **Yellow:** reference trajectory from planner
- **Green:** trajectory from running control inputs  $u[0, \dots, T - 1]$  computed by MPC based on system model for lookahead horizon  $T$



# MPC Formulations

- Linear MPC (no constraints)

- $\min_{U=\{u_t, \dots, u_{t+T-1}\}} J(x(t), U) = x_{t+T}^T Q_f x_{t+T} + \sum_{j=t}^{t+T-1} (x_j^T Q x_j + u_j^T R u_j)$
- s.t. for  $t \leq j \leq t + T - 1$
- $x_{j+1} = A x_j + B u_j$
- $x_j$  is the difference between actual state and ref state, which should be minimized with the term  $x_{t+T}^T Q_f x_{t+T}$
- $u_j$  is control input, which should be minimized with the term  $u_j^T R u_j$  (e.g., to save fuel)
- Relative magnitudes of  $Q$  and  $R$  encode relative importance of the two objectives
- Can be solved analytically  $u_t = -K x_t$  with Linear Quadratic Regulator (LQR)

- Nonlinear MPC (with constraints)  $\min_{U=\{u_t, \dots, u_{t+T-1}\}} J(x(t), U) = \sum_{j=t}^{t+T} C(x_j, u_j)$

- s.t. for  $t \leq j \leq t + T - 1$
- $x_{j+1} = f(x_j, u_j)$
- $x_{min} \leq x_{j+1} \leq x_{max}$
- $u_{min} \leq u_j \leq u_{max}$
- $g(x_j, u_j) \leq 0$
- $h(x_j, u_j) = 0$
- Both objective  $J(x(t), U)$  and system dynamics  $f(x_j, u_j)$  may be nonlinear.

- Note: in  $x_{t+T}^T$ , superscript  $T$  denotes “vector transpose”; subscript  $T$  denotes “lookahead horizon”;

# MPC Pros and Cons

- Pros

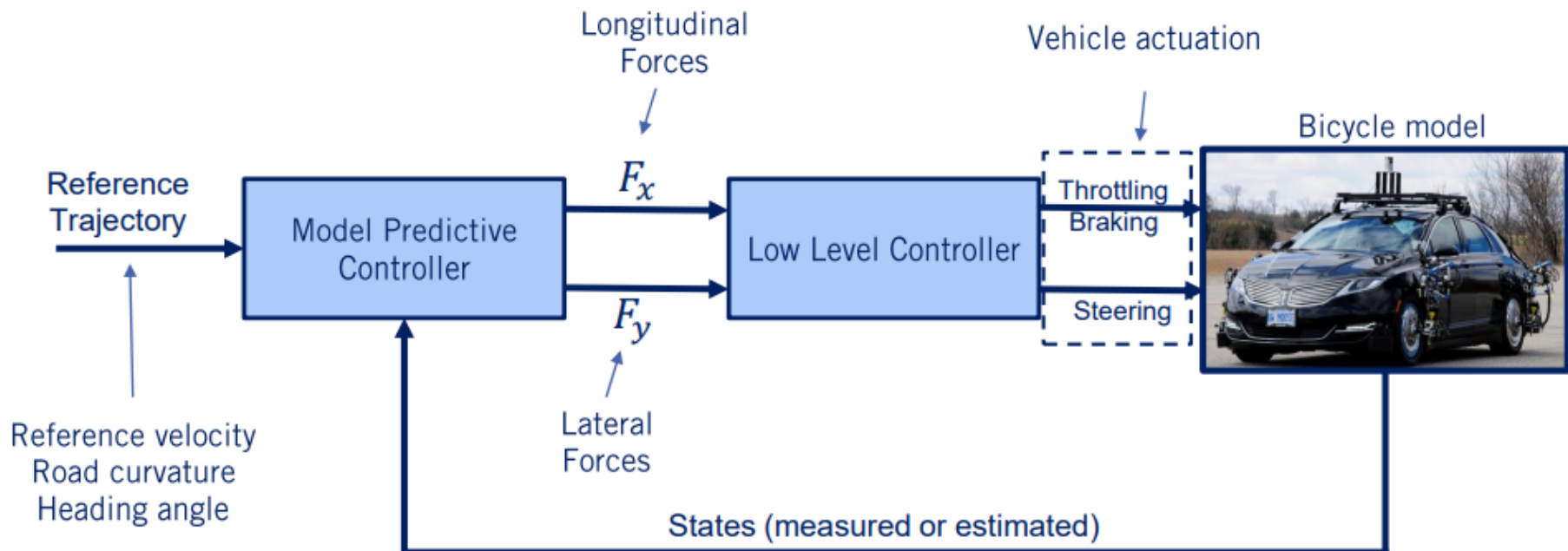
- Predictive control with lookahead.
  - PID control is like driving your car by looking in the rearview mirror.
- Handles constraints explicitly.
  - PID control cannot handle constraints.
- Applicable to both linear and nonlinear systems.
  - Pole placement for PID control design is applicable to linear systems only.

- Cons

- Optimizer computation may be expensive.
  - Especially for non-linear MPC.
  - Select lookahead horizon  $T$  to tradeoff between control performance and computation overhead; Larger  $T \rightarrow$  better control performance but higher overhead.
- Requires accurate yet efficient system model.

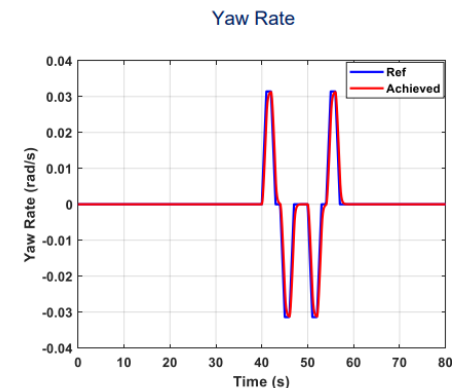
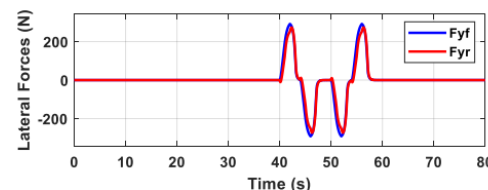
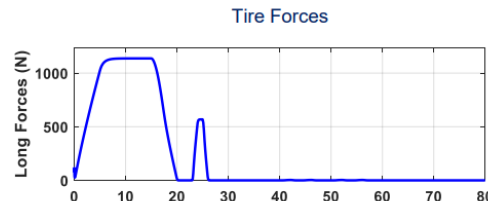
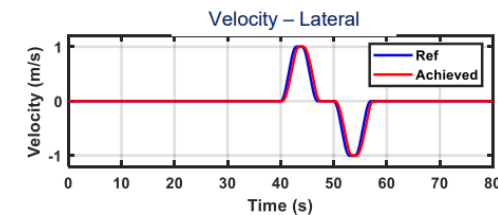
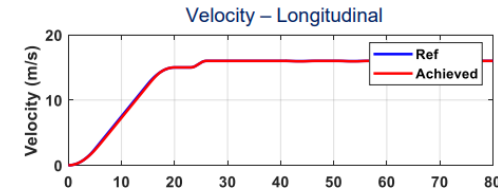
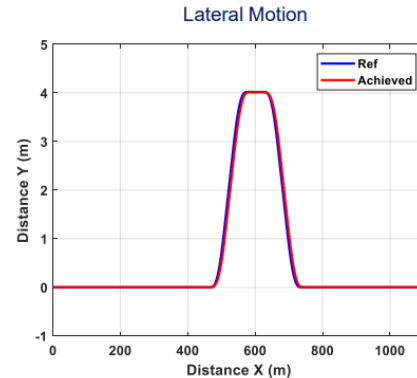
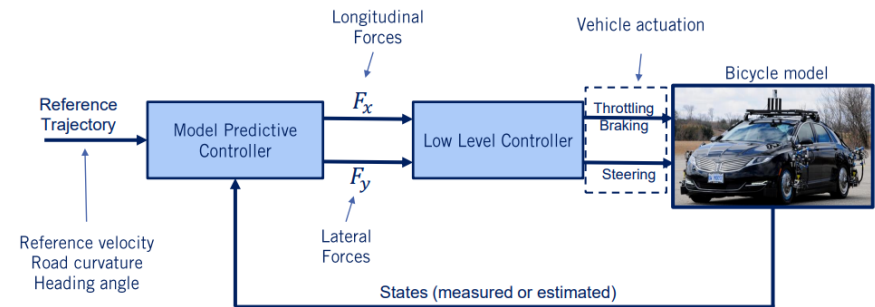
# MPC Example: Vehicle Lateral Control

- MPC cost function: minimize
  - Deviation from desired reference trajectory
  - Minimization of control effort (to save fuel)
- MPC constraints:
  - System dynamics (longitudinal and lateral)
  - Tire force limits
- Low-level controller takes into account:
  - Engine map (a lookup table)
  - Actuator models
  - Tire force models
- It is possible to integrate low-level controller into MPC, so the overall MPC has more complex models and constraints, with increased optimizer computation load.



# MPC Example Performance

- This is a passing maneuver: ego vehicle turns left to pass a front vehicle, and then turns right to return to ego-lane.
- MPC controller performance
  - Actual vehicle state trajectories (lateral position  $y$ , longitudinal and lateral velocities, yaw rate (angular velocity)) (blue) track ref trajectories (ref) well
- Low-level controller performance
  - Actual tire forces (blue) track ref tire forces  $F_x, F_y$  (ref) well





# MPC Quiz

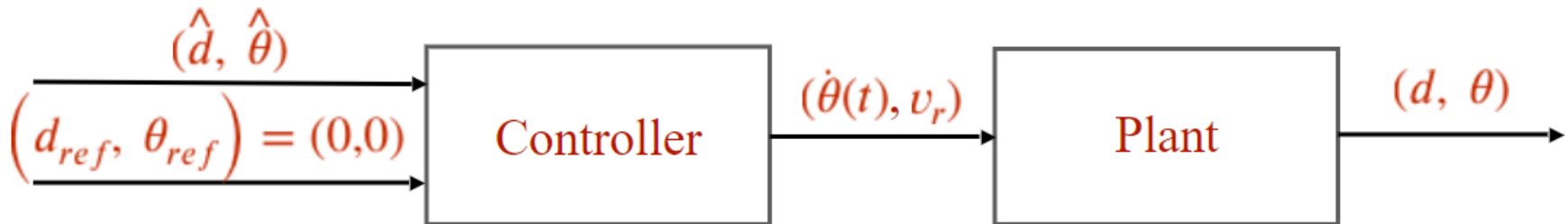
- Which from the below statement about MPC are true?
  - 1) Horizon is a finite window of time
  - 2) Prediction horizon keeps being shifted at each time step
  - 3) Full optimization over the time horizon is performed at each iteration
  - 4) Only the first control action from the optimization is applied at time  $t$
  - 5) All of the above
- ANS: 5



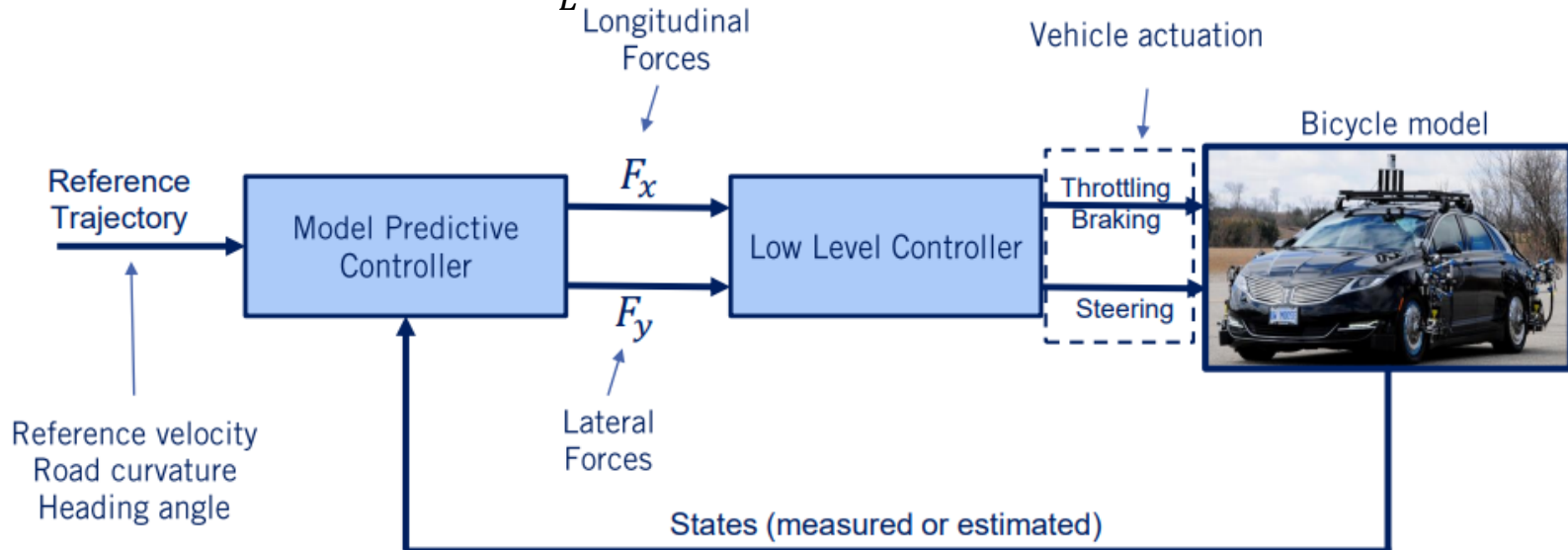
# Kinematics vs. Dynamics

- Kinematics is study of motion without considering the forces that affect the motion. It deals with the geometric relationships that govern the system
  - A kinematic model:  $\dot{x} = v, \dot{v} = \dot{x} = a$
  - Uses position, velocity, acceleration (and/or further derivatives) as control input (e.g. the kinematic bicycle model)
- Dynamics is the study of motion taking into account the forces that affect it. It is described by the equations of motion.
  - A dynamic model:  $F = M\ddot{x} + B\dot{x}$  (Newton's law with friction)
  - Uses force and torque as control input, and takes mass and inertia into consideration.
  - e.g., vehicle dynamics model (longitudinal and lateral)
- Consider two vehicles with the same geometry but different mass/weight turning a tight corner
  - They may have the same kinematic model, but different dynamic model due to different mass  $M$ .
  - If both are controllable kinematically by control input  $a$ :
    - The light vehicle may be controllable dynamically by control input  $F$ .
    - The heavy vehicle may not be controllable dynamically by control input  $F$ . Due to large  $M$ ,  $F$  may exceed the max actuator limit.
- Orthogonal issue from control algorithm
  - A control algorithm, e.g., PID or MPC, may be either kinematic or dynamic control

# Kinematic vs. Dynamic Control



PID controller for kinematic bicycle model with heading angle rate ( $\dot{\theta}$ ) and velocity ( $v_r$ , constant here) as control input. ( $\dot{\theta}$  should be controlled indirectly by controlling steering angle  $\delta$ , with  $\dot{\theta} = \frac{v \tan \delta}{L}$ .)



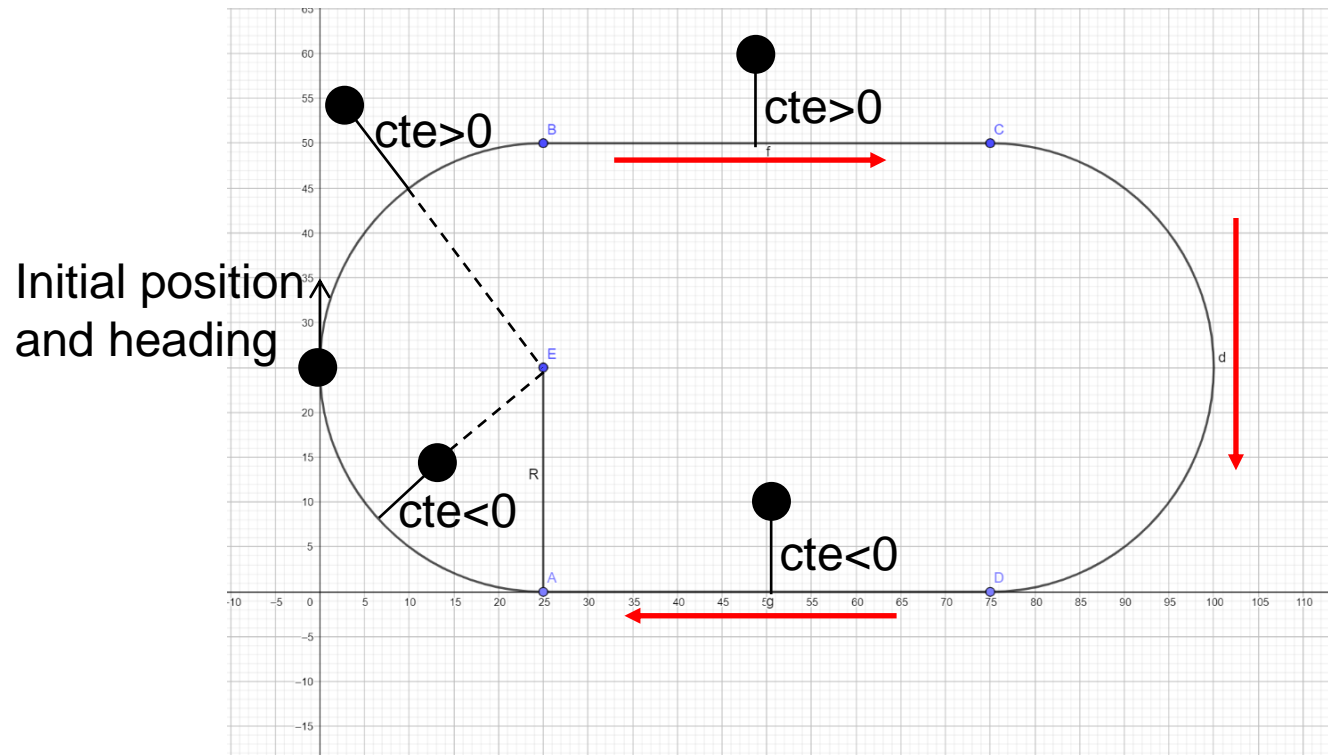
MPC for dynamic vehicle model (high-level controller) with forces (longitudinal and lateral) as control input.

# PID Control Lab Setup

- Based on Udacity course Lesson AI for Robotics, Lesson 15: PID Control
  - <https://classroom.udacity.com/courses/cs373/>
- Lateral control of a car to run along a race track (either straight line or circular) with fixed speed.

# Udacity: Racetrack Control

- Lesson 16: Problem Set 5, 4. Quiz: Racetrack control.
- Cross-track error (cte): lateral distance (of rear wheel) to desired trajectory, defined as:
  - if  $x \in [radius, 3 * radius]$ : deviation from the straight horizontal track.
  - Otherwise: deviation from each semi-circle track.
- For clockwise traversal,  $cte > 0$  if car is outside of the track region;  $cte < 0$  if inside.

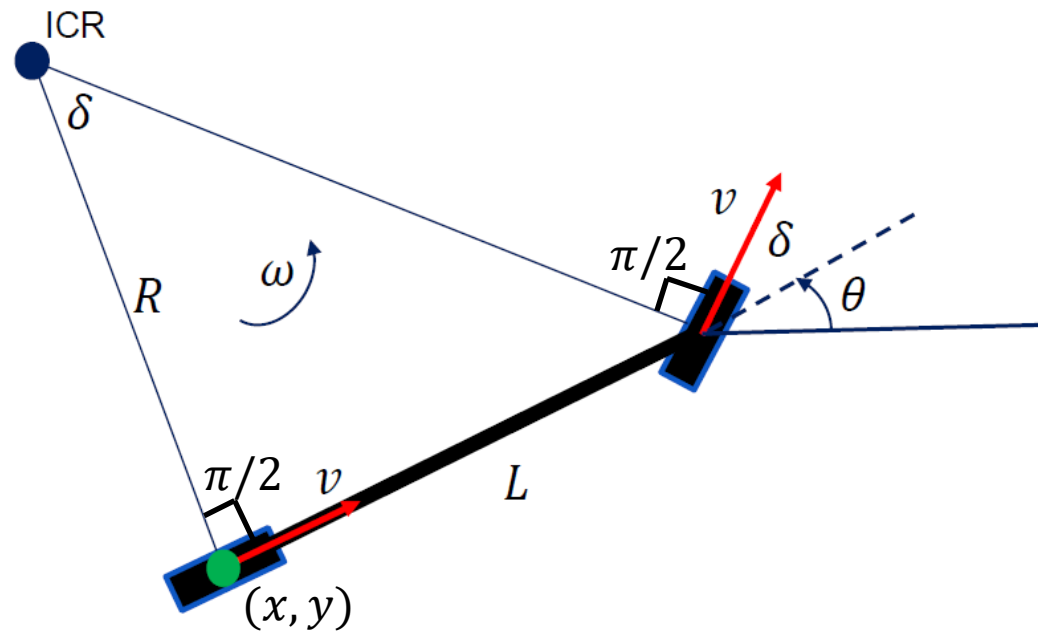


# Kinematic Bicycle Model

- Front wheel steering. Assuming here rear wheel as reference point (may also use front wheel or center of gravity).
- State vector:  $[x \ y \ \theta]^T$ : vehicle pose includes its position  $(x, y)$  and heading angle  $\theta$ .
- Control inputs:  $[\delta \ v]^T$ : steering angle  $\delta$  and vehicle speed  $v$  (assumed to be constant).
- $\tan \delta = \frac{L}{R}$ 
  - $L$ : vehicle length (distance between 2 wheels);  $R$ : rotation radius of Instantaneous Center of Rotation (ICR), equal to distance between ICR and rear wheel. Curvature  $\kappa = \frac{1}{R}$ .
  - Line from ICR to each wheel is perpendicular to it.
- $\dot{\theta} = \omega = \frac{v}{R} = \frac{v \tan \delta}{L}$ 
  - Angular velocity is speed  $v$  divided by rotation radius  $R$
- Typically, angles  $\delta, \theta$  are based on counter-clockwise convention w.r.t reference direction.
  - In the fig,  $\delta \approx \frac{\pi}{6}$  w.r.t ref direction  $v$ ;  $\theta \approx \frac{\pi}{6}$  w.r.t ref direction east (horizontal);  $\dot{\theta} > 0$  for counter-clockwise rotation.

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = v \begin{bmatrix} \cos \theta \\ \sin \theta \\ \frac{\tan \delta}{L} \end{bmatrix}$$

(Non-linear in  $\delta$ ;  
Linear in  $v$ )



# State Update Equation

- Circular motion around ICR (accurate):

- $$\begin{bmatrix} x(t + dt) \\ y(t + dt) \\ \theta(t + dt) \end{bmatrix} = \begin{bmatrix} x(t) - R \sin \theta + R \sin(\theta + \dot{\theta} dt) \\ y(t) + R \cos \theta - R \cos(\theta + \dot{\theta} dt) \\ \theta + \dot{\theta} dt \end{bmatrix}$$

- $R = \frac{L}{\tan \delta} = \frac{v}{\dot{\theta}}$

- Straight-line motion for small  $\dot{\theta} dt$  (approximate):

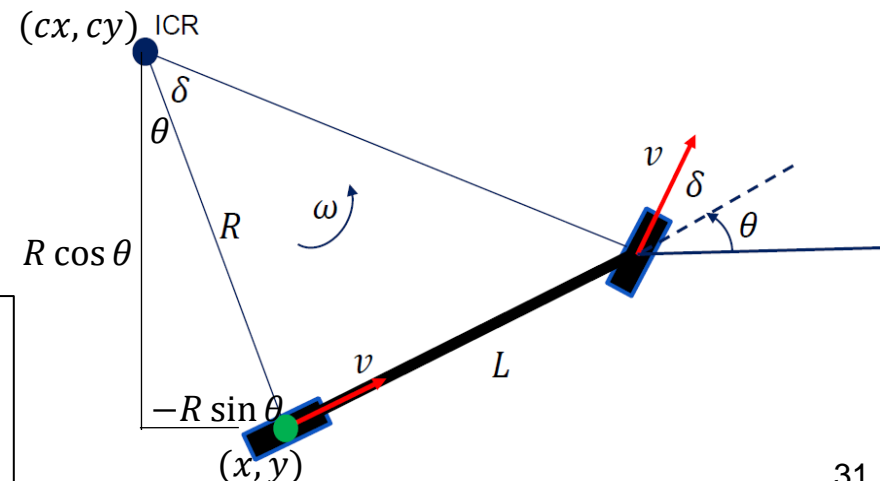
- $$\begin{bmatrix} x(t + dt) \\ y(t + dt) \\ \theta(t + dt) \end{bmatrix} = \begin{bmatrix} x(t) + v dt \cos \theta \\ y(t) + v dt \sin \theta \\ \theta + \dot{\theta} dt \end{bmatrix}$$

- $\delta \rightarrow 0, \dot{\theta} dt \rightarrow 0$

# Udacity: State Update based on Kinematic Bicycle Model

- # apply noise
- steering2 = random.gauss(steering, self.steering\_noise)
- distance2 = random.gauss(distance, self.distance\_noise)
- # apply steering drift
- steering2 += self.steering\_drift
- # noise and drift are all set to 0, so steering2 is steering angle  $\delta$ , distance2 is distance traveled per time step  $vdt$
- # Execute motion
- turn = np.tan(steering2) \* distance2 / self.length ( $\dot{\theta}dt = \frac{vdt \tan \delta}{L}$ )
- **if abs(turn) < tolerance:** (with small  $\dot{\theta}dt$ )
- # approximate by straight line motion
- self.x += distance2 \* np.cos(self.orientation) ( $x += vdt \cos \theta$ )
- self.y += distance2 \* np.sin(self.orientation) ( $y += vdt \sin \theta$ )
- self.orientation = (self.orientation + turn) % (2.0 \* np.pi) ( $\theta += \dot{\theta}dt$ )

- **else:** (with large  $\dot{\theta}dt$ )
- # Circular motion around ICR
- radius = distance2 / turn ( $R = \frac{v}{\dot{\theta}}$ ; can also use  $R = \frac{L}{\tan \delta}$ )
- # compute ICR's coordinates (cx, cy)
- cx = self.x - (np.sin(self.orientation) \* radius) ( $cx = x - R \sin \theta$ )
- cy = self.y + (np.cos(self.orientation) \* radius) ( $cy = y + R \cos \theta$ )
- self.orientation = (self.orientation + turn) % (2.0 \* np.pi) ( $\theta += \dot{\theta}dt$ )
- # compute vehicle's x, y coordinate after rotation around ICR
- self.x = cx + (np.sin(self.orientation) \* radius) ( $x = cx + R \sin \theta$ )
- self.y = cy - (np.cos(self.orientation) \* radius) ( $y = cy - R \cos \theta$ )



The “modulo  $2\pi$ ” operations keep angles to be within  $2\pi$ ; they are omitted or implicitly assumed in the state update equations, as they do not affect results of cos, sin functions (assuming no numeric overflow).

# Straight Line vs. Circular Motion

- Straight line motion (with steering angle  $\delta = 0$ ) is a special case of circular motion with radius  $\infty$ .
  - $\delta \rightarrow 0 \Rightarrow R = \frac{L}{\tan \delta} \rightarrow \infty, \dot{\theta} = \frac{v}{R} \rightarrow 0$  (small steering angle  $\delta$  leads to slow angular velocity  $\dot{\theta}$ .)
  - We use this special case to improve computational efficiency for small  $\delta, \dot{\theta}$ , and avoid division by 0.
- $x(t + dt) = x(t) - R \sin \theta + R \sin(\theta + \dot{\theta} dt) = x + R(\sin(\theta + \dot{\theta} dt) - \sin \theta) = x + \frac{v}{\dot{\theta}} * \cos \theta * \dot{\theta} dt = x + v dt \cos \theta$ 
  - $\sin(\theta + \dot{\theta} dt) - \sin \theta \approx \frac{d}{dt} \sin \theta * \dot{\theta} dt = \cos \theta * \dot{\theta} dt$ , for small  $\dot{\theta} dt$ .
- $y(t + dt) = y(t) + R \cos \theta - R \cos(\theta + \dot{\theta} dt) = y - R(\cos(\theta + \dot{\theta} dt) - \cos \theta) = y + \frac{v}{\dot{\theta}} * \sin \theta * \dot{\theta} dt = y + v dt \sin \theta$ 
  - $\cos(\theta + \dot{\theta} dt) - \cos \theta \approx \frac{d}{dt} \cos \theta * \dot{\theta} dt = -\sin \theta * \dot{\theta} dt$ , for small  $\dot{\theta} dt$ .
- Four special cases of straight line motion:
  - $\theta = 0 \Rightarrow x' = x + v dt, y' = y$  (east)
  - $\theta = \pi \Rightarrow x' = x - v dt, y' = y$  (west)
  - $\theta = \frac{\pi}{2} \Rightarrow x' = x, y' = y + v dt$  (north)
  - $\theta = \frac{3\pi}{2} \Rightarrow x' = x, y' = y - v dt$  (south)



# run()

- Implements the PID controller for with PID gains
  - $\text{params}[0]$  as  $K_p$ ;  $\text{params}[1]$  as  $K_d$ ;  $\text{params}[2]$  as  $K_i$ . (Minus signs can be removed without affecting correctness.)
  - Returns actual trajectory as arrays of  $x\_trajectory[]$ ,  $y\_trajectory[]$ ; and average error, defined as sum of squared cte.
- For clockwise travel direction:
  - If  $\text{cte} > 0$ , car is outside of track region; steering angle  $\delta$  should decrease (turn right according to the counter-clockwise convention).
  - If  $\text{cte} < 0$ , car is inside of track region; steering angle  $\delta$  should increase (turn left).
  - Based on the above,  $K_p$  should be positive (this can be a sanity check for your final solution).

```
def run(robot, params, n=100, speed=1.0):
    x_trajectory = []
    y_trajectory = []
    err = 0
    # TODO: your code here
    prev_cte = robot.y
    int_cte = 0
    for i in range(2 * n):
        cte = robot.y
        diff_cte = cte - prev_cte
        int_cte += cte
        prev_cte = cte
        steer = -params[0] * cte - params[1] * diff_cte - params[2] * int_cte
        robot.move(steer, speed)
        x_trajectory.append(robot.x)
        y_trajectory.append(robot.y)
        if i >= n:
            err += cte ** 2
    return x_trajectory, y_trajectory, err / n
```

This is for straight line track; need to call `myrobot.cte()` for circular track.

PID control law

# For General $dt$

- The Python code assumes controller time step size  $dt = 1$ .
  - Also,  $v$  is constant.  $\delta$ 's range is unconstrained (steering wheel can be turned to arbitrary angle).
- For general  $dt$ , the following needs to be modified:
  - Call `myrobot.move(steer, speed*dt)`, to match its definition `move(self, steering, distance,...)`
  - In the PID control law:
    - $diffcte = \frac{cte - prevcte}{dt}, intcte += cte * dt$

# twiddle()

Adjust each  $p[i]$  in turn.

Adjust  $p[i]$  to  $p[i] + dp[i]$  and `run()`. If error decreases, we adjusted in the right direction, keep the original adjustment  $p[i] + dp[i]$ , and increase step size to  $1.1 * dp[i]$ .

If error increases, we adjusted in the wrong direction, adjust in the opposite direction to  $p[i] - 2 * dp[i]$ . Run again.

If error decreases, we adjusted in the right direction, keep the original adjustment  $p[i] + dp[i]$ , and increase step size to  $1.1 * dp[i]$ .

If error increases, we adjusted in the wrong direction, reduce step size to  $.9 * dp[i]$ . We do not reverse direction here to avoid oscillation around current  $p[i]$  with no progress.

```
def twiddle(tol=0.2):  
    # TODO: Add code here  
    # Don't forget to call 'make_robot' before you call 'run'!  
    p = [0.0, 0.0, 0.0]  
    dp = [1.0, 1.0, 1.0]  
    robot = make_robot()  
    x_trajectory, y_trajectory, best_err = run(robot, p)  
  
    it = 0  
    while sum(dp) > tol:  
        # print("Iteration {}, best error = {}".format(it, best_err))  
        for i in range(len(p)):  
            p[i] += dp[i]  
            robot = make_robot()  
            x_trajectory, y_trajectory, err = run(robot, p)  
  
            if err < best_err:  
                best_err = err  
                dp[i] *= 1.1  
            else:  
                p[i] -= 2 * dp[i]  
                robot = make_robot()  
                x_trajectory, y_trajectory, err = run(robot, p)  
  
                if err < best_err:  
                    best_err = err  
                    dp[i] *= 1.1  
                else:  
                    p[i] += dp[i]  
                    dp[i] *= 0.9  
  
            it += 1  
    return p, best_err
```

# twiddle() vs. Pole Placement

- “Gradient descent” approach to tuning PID controller (model-free), by adjusting each PID gain parameter systematically, gradually decreasing or increasing step of adjustment  $dp[i]$  (the gradient) until convergence to minimum `best_err`.
- Pole placement for PID controller design is model-based, but requires a linear model

$$- \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = v \begin{bmatrix} \cos \theta \\ \sin \theta \\ \frac{\tan \delta}{L} \end{bmatrix} \approx \begin{bmatrix} v \\ v\theta \\ u \end{bmatrix}$$

– With simplifying assumptions:

- $\theta$  is small
- Simplified kinematic model:  $u = \dot{\theta}$  as control input instead of  $\delta$ .

# Changing to P Control

- Setting  $dparams[1] = dparams[2] = 0$  turns it into a P controller, since  $K_d, K_i$  are initialized to 0 and never changed.  $P_p$  is adjusted in `twiddle()`
- `twiddle()` is a local optimization algorithm, so perf is dependent on parameter initialization. Here are initialized to 0 for simplicity.
  - <https://classroom.udacity.com/courses/cs373/lessons/48743150/concepts/f9fe06f9-9b1c-40b1-b9ad-312ca92be287>

#### ENTER CODE BELOW THIS LINE

```
n_params = 3
dparams   = [1.0 for row in range(n_params)]
params    = [0.0 for row in range(n_params)]
dparams[2] = 0.0
dparams[1] = 0.0
```

```
best_error = run(params)
n = 0
while sum(dparams) > tol:
    for i in range(len(params)):
```