

# 3. Longitudinal & Lateral Control

## 第3课：纵向、横向控制

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- Architecture of autonomous driving
  - How human drive
  - How a computer drives
  - Decision-making architecture
- Action
  - Trajectory tracking
  - Trajectory planning
  - Route planning
  - Trip planning

# Outline

- Longitudinal control
  - Speed tracking
  - Trajectory tracking
  - Vehicle following
- Lateral control
  - Lane keeping
  - Lane changing

# Longitudinal & lateral control

## Longitudinal control

- Device: throttle, brake, (clutch)
- Action: push/release pedals
- Influences speed and position



## Lateral control

- Device: steering wheel
- Action: turn steering wheel
- Influences angular velocity and direction



# Longitudinal control 纵向控制

- Speed tracking
- Position tracking
- Vehicle following
- Further discussions

# Decision-making problem

- Data
  - Vehicle parameters
  - How you want the vehicle to move
- Decision variables
  - Torque generated by the engine
- Constraints
  - Vehicle dynamics
- Objective
  - Make the vehicle move as you want
- Reference:
  - Attia, R., Orjuela, R., & Basset, M. (2014). Combined longitudinal and lateral control for automated vehicle guidance. *Vehicle System Dynamics*, 52(2), 261-279.

# Longitudinal dynamics #

- Vehicle mass =  $m$  [kg]
- Vehicle speed =  $v$  [m/s]
- Propelling force =  $F_p$  [N]
- Aggregate resisting force =  $F_r$  [N]
  - Aerodynamic force  $F_a = 1/2 \rho C_d v^2$
  - Gravitational force  $F_g = mg \sin \theta$
  - Rolling resistance force  $F_{rr} = C_r mg \cos \theta$
- Dynamic equation

$$m\dot{v} = F_p - F_r$$

where  $\dot{v}$  is the time-derivative of  $v$ , i.e., the acceleration.

(# in the title means blackboard demonstration)

# Longitudinal dynamics #

- Propelling dynamics

- Moment of inertia of wheel =  $I_w$
- Rotational speed of wheel =  $\omega$
- Longitudinal force from the ground =  $F_l$
- Radius of wheel =  $R$
- Traction torque =  $T_c$
- Brake torque =  $T_b$

$$I_w \dot{\omega} = -F_l R + T_c - T_b$$

- Assume non-slip rolling:

- $v = R\omega$
- $F_p = F_l$

- Assume no power transmission losses

- $\omega = R_g \omega_e$  ( $R_g$  = gearbox ratio)
- $T_e = R_g T_c$  ( $T_e$  = engine torque)



# Longitudinal dynamics

- Longitudinal dynamics for synthesis

$$\frac{(mR^2 + I_w)R_g}{R} \dot{v} = T_e - R_g T_b - R_g R F_r$$

- Let  $M_t = \frac{(mR^2 + I_w)R_g}{R}$ , we have *state-dependent*

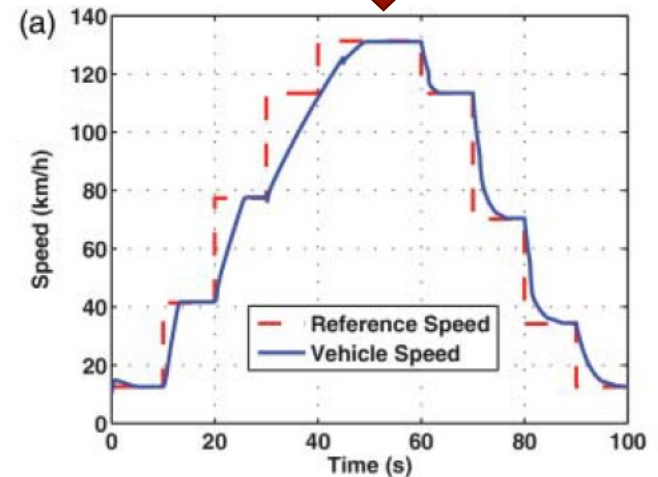
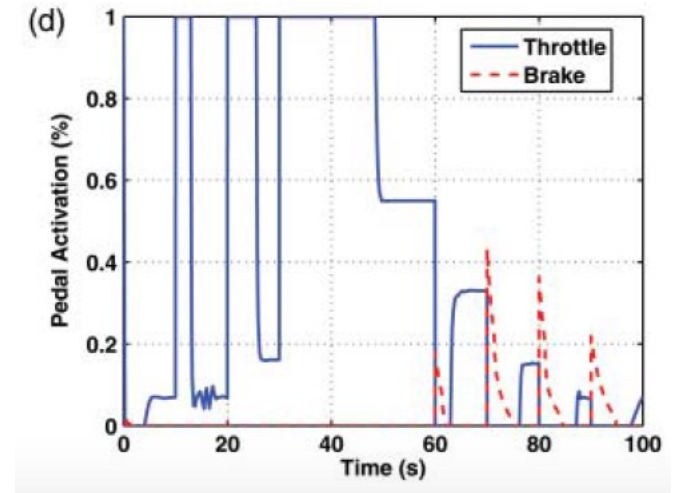
$$\dot{v} = \frac{1}{M_t} (T_e - R_g T_b - R_g R F_r)$$

*state & output*      *input*

- Main messages
  - We can tune the *speed* by playing with the *engine torque*
  - Such influence is indirect; we can directly set  $\dot{v}$  but not  $v$
  - Recall that the resisting force  $F_r$  depends on speed (through aerodynamic force)

# Speed tracking

- So how should we set the control input, i.e., the engine torque?
- It depends on how you want the vehicle to move.
- A simple objective:
  - You have a **pre-defined** reference speed profile  $v_{ref}(t)$  for  $t \geq 0$
  - You want the vehicle to track the pre-defined speed profile
  - **Track** means **asymptotical convergence**.



# Speed tracking

- Data
  - Vehicle parameters
  - Reference speed profile  $v_{ref}(t)$  for  $t \geq 0$
- Decision variables
  - Torque generated by the engine
  - Equivalently, pedal movement: push throttle/brake to some angle...
  - Assume automatic transmission; no gear switch & no clutch...
- Constraints
  - Vehicle dynamics
- Objective
  - Make the actual vehicle speed  $v(t)$  asymptotically converge to the reference speed  $v_{ref}(t)$ , i.e., “tracking”

# Speed tracking

- Let's discuss insights before getting into the math.
- Basically, we want to drive the tracking error

$$e(t) = v_{ref}(t) - v(t)$$

to zero.

- Intuitively,
  - If  $v(t) < v_{ref}(t)$ , i.e., if actual speed < desired speed, then we want **push throttle forward** and apply more torque;
  - If  $v(t) > v_{ref}(t)$ , i.e., if actual speed > desired speed, then we want **release throttle backward** and apply less torque or disengage throttle and push brake;
  - If  $v(t) = v_{ref}(t)$ , i.e., if actual speed = desired speed, then we want to **keep the current position** of throttle/brake.

# Speed tracking

- So, how to quantitatively implement the above insights?
- That is, if we observe  $v(t)$  and compute  $e(t) = v_{ref}(t) - v(t)$ , how should we exactly select the torque or the throttle/brake position?
- Essentially, we need a **mapping** from our observation to our decision.
- Such a mapping is called a **controller**.
- Also called a **control policy** or **control law**.



# Speed tracking

- Let's clarify several definitions before proceeding...
- Input 输入: something that you or the environment injects into the system
- Output 输出: something that you observe from the system
- State 状态:
  - Physical interpretation: a set of information that describes the current status, configuration, condition etc. of a system.
  - Mathematical interpretation: a set of variables that, along with control inputs, uniquely specifies the system's output in the future.

# Speed tracking

- The speed tracking problem is essentially the determination of the controller, which specifies the decision (action) according to the observed information (state).
- Formally, a controller is a **function** that maps states to actions.
- The process of designing this function is called **control synthesis**.
- If the function is linear -> linear control
- If the function is non-linear -> nonlinear control
- If the function is learned from data -> learning-based control

# Speed tracking

- So, how can we synthesize a speed tracking controller?
  - Linear? Non-linear?
  - Parameter values?
- Recall our objective: make the actual speed  $v(t)$  track the reference speed  $v_{ref}(t)$ .
- Equivalently, we want the tracking error  $e(t)$  to vanish.

$$e(t) = v_{ref}(t) - v(t)$$

$$\dot{v} = \frac{1}{M_t} (T_e - R_g T_b - R_g R F_r)$$

$$\dot{e}(t) = \dot{v}_{ref}(t) - \frac{1}{M_t} (T_e(t) - R_g T_b - R_g R F_r(t))$$



# Speed tracking

- I claim that the following controller can achieve what we want

$$T_e(t) = M_t \left( ke(t) + \dot{v}_{ref}(t) \right) + R_g R F_r(t)$$

where  $k$  is some positive constant.

- When tracking error  $e$  is large, we need to increase  $T_e$ .
- When reference speed  $v_{ref}$  is increasing, we need to increase  $T_e$
- When resisting force  $F_r$  is large, we need to increase  $T_e$
- Why this particular form of controller? (Not required in this course.)

# Speed tracking: some nonlinear control theory #\*

- Consider a Lyapunov function

$$V = \frac{1}{2}e^2.$$

- If you plug the controller

$$T_e(t) = M_t \left( ke(t) + \dot{v}_{ref}(t) \right) + R_g R F_r(t)$$

into the dynamic equation

$$\dot{e}(t) = \dot{v}_{ref}(t) - \frac{1}{M_t} \left( T_e(t) - R_g T_b - R_g R F_r(t) \right),$$

you will find that

$$\dot{V}(t) = e(t)\dot{e}(t) = -\frac{k}{2} \left( e(t) \right)^2 = -kV(t).$$

(\* means advanced materials not required in this course)

# Speed tracking: some nonlinear control theory #\*

- Recall results from ordinary differential equations
- Solution to

$$\frac{d}{dt}V(t) = -kV(t)$$

is

$$V(t) = V(0) \exp(-kt) .$$

- The above can be re-written as

$$\begin{aligned} (e(t))^2 &= (e(0))^2 \exp(-kt) \\ e(t) &= e(0) \exp(-kt/2) \end{aligned}$$

- That is, the tracking error  $e(t)$  exponentially converges towards 0.

# Homework 1

- Write codes that simulates the dynamics of the speed tracking problem.
- Verify that the claimed controller is exponentially convergent.
- For your convenience, let's simplify the problem a bit.
- We re-write the dynamic equation

$$\dot{v} = \frac{1}{M_t} (T_e - R_g T_b - R_g R F_r)$$

as

$$\dot{v} = \alpha(T_e - \beta - \gamma v^2)$$

and let  $\alpha = \beta = \gamma = 1$ .

# Homework 1

## Problem 1: Speed tracking

- **Part a:** Reformulate the problem in discrete time (so that you can code).

- Suppose that you have an ODE

$$\frac{d}{dt}x(t) = f(x(t)).$$

- You can discretize it as

$$\frac{x(t + \Delta t) - x(t)}{\Delta t} = f(x(t)).$$

- So, the discrete dynamic equation is

$$x(t + \Delta t) = x(t) + f(x(t))\Delta t.$$

- This is how you can update the state in Python/Matlab/C++...

- Hint: your response should be in this form:

$$v(t + \Delta t) = v(t) + f(v(t))\Delta t$$

# Homework 1

- **Part b:** Find a controller  $T_e$  such that

$$e(t)\dot{e}(t) = -\frac{1}{2}(e(t))^2.$$

- **Part c:** Assume  $v_{ref}(t) = 1$  for all  $t \geq 0$ . Assume zero initial condition, i.e.,  $v(0) = 0$ . Simulate the ODE

$$\dot{v}(t) = \alpha(T_e(t) - \beta - \gamma v(t)^2)$$

with the controller that you found in part 2. Plot  $v(t)$  vs.  $t$  and label  $v_{ref}$ ; please also label the axes!

- **Part d:** Select a time-varying reference speed  $v_{ref}(t)$  and see if your controller still works. (Everyone should have his/her unique reference speed profile.) Plot  $v(t)$  vs.  $t$  and label  $v_{ref}$ .

# Position tracking

- Data
  - Vehicle parameters
  - Reference position profile  $x_{ref}(t)$  for  $t \geq 0$
- Decision variables
  - Pedal movement: push throttle/brake to some angle...
- Constraints
  - Vehicle dynamics
- Objective
  - Make the actual position  $x(t)$  asymptotically converge to the reference position  $x_{ref}(t)$ , i.e., “tracking”

# Position tracking

- Step 1: generate speed profile
  - Assume  $\Delta = 1$  (unit time step)
  - Suppose a position profile  $x(0), x(1), x(2), \dots$
  - A simple (but not always feasible) scheme:
$$v(t) = x(t + 1) - x(t)$$
  - As long as the position profile is not bizarre, the above scheme should be OK.
  - You can say that the above scheme is a **speed controller!**  
Speed controller: position  $\rightarrow$  speed
- Step 2: use the speed tracking strategy that we discussed before.



# Homework 1

## Problem 2: trajectory tracking

- **Part a**: Select a **linear** position profile, generate a corresponding speed profile
- **Part b**: Simulate the position tracking process. (Everyone should have his/her unique reference speed profile.) Plot the position  $x(t)$  vs.  $t$  and label the reference position  $x_{ref}(t)$ .
- **Part c**: Select a **nonlinear** position profile, generate a corresponding speed profile
- **Part d**: Simulate the position tracking process. (Everyone should have his/her unique reference speed profile.) Plot the position  $x(t)$  vs.  $t$  and label the reference position  $x_{ref}(t)$ .

# Vehicle following

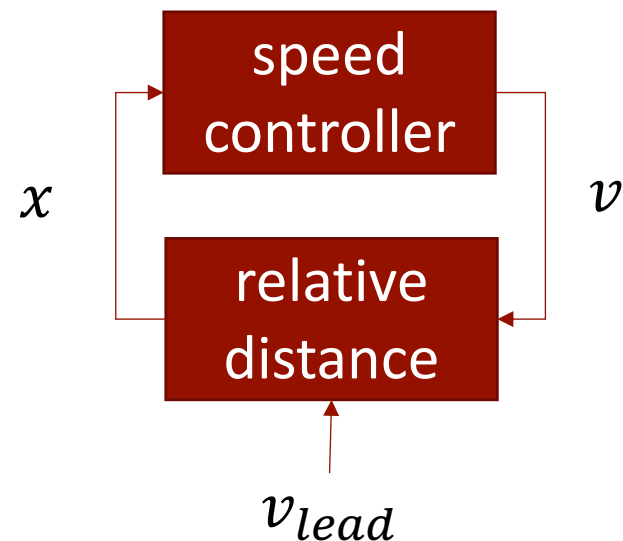
- Data
  - Vehicle parameters
  - Real-time relative position  $x_{lead}(t)$  and absolute speed  $v_{lead}(t)$  of the leading vehicle
- Decision variables
  - Pedal movement: push throttle/brake to some angle...
- Constraints
  - Vehicle dynamics
  - Safety constraints (no collision)
- Objective
  - Maintain a steady-state distance  $d$  to the leading vehicle.,  
“following”

# Vehicle following

- Differences w.r.t. position tracking
  - No pre-defined position/speed profile
  - Data received in a real-time manner rather than in a one-time manner at the beginning.
- Again, we assume **unit time step**.
- Dynamic equation
$$x(t + 1) = x(t) + v_{lead}(t) - v(t)$$
- We want  $x$  to be close to the reference distance  $d$
- Steady-state:
  - $x = d$
  - $v = v_{lead}$

# Vehicle following

- To do vehicle following, we first need a speed controller, which generates the speed  $v(t)$  according to the observation and prediction of the leading vehicle's movement.
- Again, we can consider a naïve controller
$$v(t) = x(t) + v_{lead}(t) - d$$
- Then, implement the above speed via speed tracking



# Further discussions

- Linearization 线性化
- Saturation 饱和
- Noise & perturbation 噪声、扰动
- Model identification 模型辨识
- Human driver behavior 人类驾驶行为

# Linearization

- Recall that we had a model in the form

$$\dot{v} = \alpha(T_e - \beta - \gamma v^2)$$

- This is a nonlinear ODE, which may not be easy to deal with, if the right-hand side becomes more complex.
- A common technique is to linearize the equation, i.e. applying the idea of Taylor expansion.
- Suppose that the vehicle's speed  $v$  is **not far away** from the equilibrium speed  $v_0$ .

$$\begin{aligned}\dot{v} &= \alpha \left( T_e - \beta - 2\gamma \left( v_0 + (v - v_0) \right)^2 \right) \\ &\approx \alpha \left( \textcolor{red}{T}_e - \beta - 2\gamma v_0^2 - 4\gamma v_0(\textcolor{red}{v} - v_0) \right)\end{aligned}$$

- Thus, the RHS is linear in control input and state!

# Linearization

- Why would we linearize?
- Recall that the solution to

$$\dot{x} = -kx$$

is

$$x(t) = x(0) \exp(-kt).$$

- That is, the state exponentially converges to the equilibrium, which happens to be the origin in the above ODE.
- The theory of dealing with a linear dynamical system

$$\dot{x} = ax + bu$$

is very well developed and validated in practice.

- Therefore, in many cases, linearization suffices; no nonlinear control has to be done...

# Saturation

- Recall that the torque (control input) for speed tracking is given by

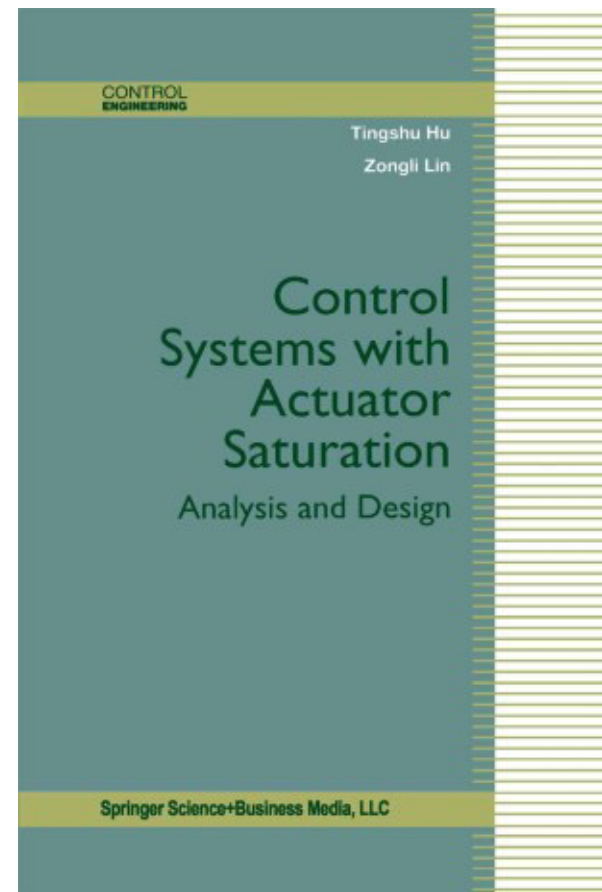
$$T_e(t) = M_t \left( k e(t) + \dot{v}_{ref}(t) \right) + R_g R F_r(t)$$

- What if the RHS in the above exceeds the maximally attainable torque?
- The attainable torque is upper-bounded by the physics of the engine.
- Let  $\bar{T}_e$  be the upper bound.
- If  $T_e \leq \bar{T}_e$ , we are good.
- If  $T_e > \bar{T}_e$ , we say the controller to be **saturated**.
- That is, the machine cannot implement our command.



# Saturation

- Saturation can be very tricky in control synthesis.
- At least, saturation slows down the system's convergence.
- Sometimes, saturation can even destabilize a system.
- Two approaches to addressing this problem
  - Lazy approach: design a controller that never reaches its limits
  - Systematic approach: incorporate the saturation nonlinearity in the design process (reachability, stabilizability, etc.)



# Homework 1

## Problem 3: Saturation

For the torque profile  $T_e(t)$  that you generated in problem 2, let

$$\bar{T}_e = 0.8 \max_t T_e(t).$$

Suppose now that the torque cannot exceed  $\bar{T}_e$ . That is, the actual torque  $T_a(t)$  is given by

$$T_a(t) = \min\{\bar{T}_e, T_e(t)\}$$

where  $T_a(t)$  is generated by the controller you obtained in Problem 2. Simulate the trajectory again and discuss the difference from the result in problem 2.

# Noise & perturbations

- Recall the dynamic equation is

$$\dot{v} = \alpha(T_e - \beta - \gamma v^2)$$

- The above assumes that the model **perfectly** matches reality.
- But this never happens. What should we do?
- A random noise can be added to the RHS!

$$\dot{v} = \alpha(T_e - \beta - \gamma v^2) + \epsilon$$

- The noise may result from
  - Modeling error
  - Unmodeled dynamics
  - Environmental perturbations
  - Observation & actuation errors

# Noise & perturbations

$$\dot{v} = \alpha(T_e - \beta - \gamma v^2) + \epsilon$$

- Control synthesis is more challenging, since everything becomes random.
- Essentially, we are no longer able to exactly tune  $v(t)$ , since the speed now becomes a **stochastic process**  $\{V(t); t \geq 0\}$ !
- Instead, we can tune its probability distribution!
- That is, we can specify the cumulative distribution function (PDF)  $F_V(v, t)$ .
- We can no longer ensure that the speed exactly tracks the reference speed profile.

# Noise & perturbations

- Instead, we can only say something as follows:
  - At time  $t$ , the probability that the actual speed lies in the interval  $(v_{ref}(t) - \delta, v_{ref}(t) + \delta]$  is given by
$$\Pr\{V(t) \in (v_{ref}(t) - \delta, v_{ref}(t) + \delta]\} \\ = F_V(v_{ref}(t) + \delta, t) - F_V(v_{ref}(t) - \delta, t)$$
  - The variance of the tracking error converges to 0, i.e.,
$$\lim_{t \rightarrow \infty} E \left[ \left( V(t) - v_{ref}(t) \right)^2 \right] = 0.$$
- In summary, when there is random noise,
  - The actual speed may or may not track the reference speed well;
  - But you can tune your controller so that the actual speed is more likely to track well than not.

# Homework 1

## Problem 4: Noise

Suppose that the update equation is

$$v(t + \Delta t) = v(t) + f(v(t))\Delta t + \epsilon,$$

where  $f$  is your response to problem 1a and  $\epsilon$  is a white noise, i.e., a normally distributed random variable with zero mean; select the variance of  $\epsilon$  on your own.

Simulate the trajectory again and discuss the difference from the result in problem 2.

# Homework requirements

- Independent work
- Only pdf files accepted
- Clearly label the problem number and your response
- Attach codes in the end
- Neat formatting is much appreciated!!!

# Model identification

- Recall the dynamic equation

$$\dot{v} = \frac{1}{M_t} (T_e - R_g T_b - R_g R F_r)$$

- In practice, how to obtain the parameters?
- An even more disturbing questions is: how do you know the form of the model is correct?
- This process is called model identification.
  - Objective 1: determine the form of the dynamic equation (linear? nonlinear?...)
  - Objective 2: determine the parameters of the dynamic equation.



# Model identification

- Classical approach: measurements & experiments
- Vehicle mass =  $m$  [kg]
- Vehicle speed =  $v$  [m/s]
- Propelling force =  $F_p$  [N]
- Aggregate resisting force =  $F_r$  [N]
  - Aerodynamic force  $F_a = 1/2\rho C_d v^2$



# Model identification

- Modern (fancier) approach: learning
- Form of dynamic equation

$$\dot{x} = f(x)$$

- We can conduct some simulations or experiments and record  $x(t)$  and  $\dot{x}(t)$  for  $t \in [0, T]$
- Then, we use a function  $\hat{f}(x; \theta)$  to approximate the actual dynamics  $f(x)$ , where  $\theta$  are parameters of the approximation function.
- A fashionable (and usually good) choice of the approximation function  $f(x)$ : **neural networks**!
- $\theta$  is determined by minimizing the error

$$\int_{t=0}^T \left( \dot{x}(t) - \hat{f}(x; \theta) \right)^2 dt$$

# Model identification

- Estimation of parameters: we can use learning again!
- This is often reasonable, since many vehicle parameters vary over time.
  - Vehicle mass varies with passengers/freight/fuel...
  - Power varies with weather/fuel...
  - Air drag varies with weather...
- Instead of estimating the parameters at one time, we can gradually learn these parameters as the vehicle moves -> **adaptive control**
- Typical paradigm for adaptive control:
  - Start with a nominal controller
  - Fine-tune the nominal controller as real-time data come in

# Model identification: Online & offline

## Offline model identification

- Dynamics and parameters that do not significantly vary over time
- Use nominal relations/values
- Everything is done before the model is used for control synthesis
- Cannot adapt to perturbations

## Online model identification

- Estimate parameters (and sometimes even dynamics) in real time, as the vehicle moves
- Mimics the learning process of a student driver
- Knowledge is updated continuously
- Can adapt to perturbations

# Lateral control

Reference: Attia, R., Orjuela, R., & Basset, M. (2014). Combined longitudinal and lateral control for automated vehicle guidance. *Vehicle System Dynamics*, 52(2), 261-279.

# Lane keeping

- Data
  - Vehicle parameters
  - Geometry of the lane
- Decision variables
  - Steering wheel angle
- Constraints
  - Vehicle dynamics
- Objective
  - Keep the vehicle in the middle of the lane



# Lane changing

- Data
  - Vehicle parameters
  - Geometry of the current lane and the target lane
- Decision variables
  - Steering wheel
- Constraints
  - Vehicle dynamics
  - No interference with other vehicles
- Objective
  - Leave the current lane and join the target lane



# Summary

- Longitudinal control
  - Speed tracking
  - Trajectory tracking
  - Vehicle following
- Lateral control
  - Lane keeping
  - Lane changing



## Trajectory planning

- Single-vehicle on an empty road
  - 1 dimensional
  - 2 dimensional
- Multi-vehicle planning
- Perception
  - Onboard perception
  - Vehicle-to-vehicle connectivity
  - Vehicle-to-infrastructure connectivity