Levels of Autonomy in self-driving cars ①

Level 0: driver: driver is continuously exercising longitudinal AND lateral control
vehicle –


eyes on
hands on

Level 1: driver: driver is continuously exercising longitudinal OR lateral control
vehicle: lateral or longitudinal control is accomplished by the system

Level 2: driver: driver has to monitor the system at all times
vehicle: System has longitudinal and lateral control in a specific use case


temporary hands off

Level 3: driver: does not have to monitor the system at all times; must always be in a position to resume control
vehicle: lvl 2 + System recognizes the perf limits and request driver to resume control within a sufficient margin

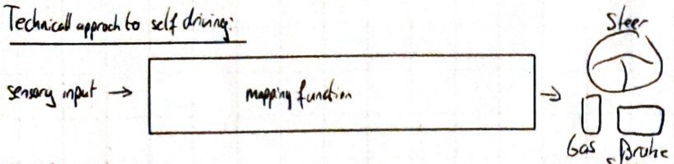
Level 4: driver: not required during defined use case
vehicle: system can cope with all situations automatically in a defined use case


eyes off
hands off

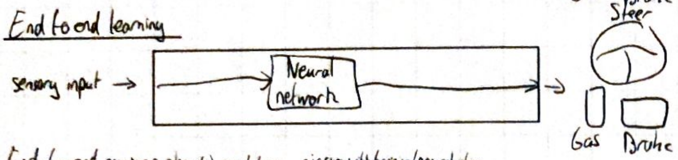
lvl 5: driver –
vehicle: System can cope with all situations during the entire journey. No driver required

Mercedes S class 2014: 2   Tesla model S: 2

Technical approach to self driving:

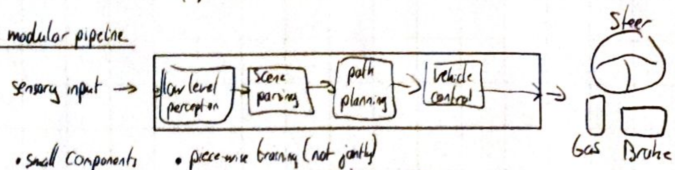


End to end learning



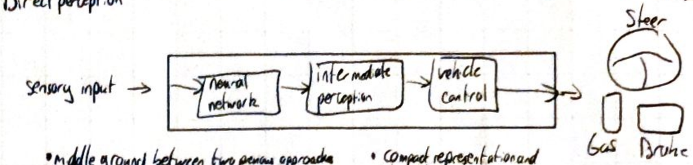
- End-to-end requires cheaper annotations
- issues with training/generalisation
- lack of interpretability...

The modular pipeline



- small components
- interpretability
- piece-wise training (not jointly)
- Path planning (and localisation) relies on HD maps
  (HD maps: centimeter precision lanes, markings, traffic lights/signs, human annotated)

Direct perception



- middle ground between two previous approaches
- compact representation and interpretability
- control is not learnt jointly
- representation can be difficult to choose

Gap 8 basé sur FreeRTOS ②

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③

Direct perception: + et – des deux autres méthodes : modular pipeline: modular, interpretable, expert decision, piece-wise training

imitation learning/reinforcement learning: end to end, simple, generalisation, interpretable, Data

→ hybrid model between end-to-end and modular pipelines
→ learning how to predict low-dimensional intermediate representations
→ decoupling perception from planning and control
→ allows to exploit classical controllers or learned controllers (or a mix)

Affordances ex. (= accessibilité): • distance to centerline • relative angle to the road • distance to lead vehicle • speed signs • traffic lights • hazard stop (pedestrians)

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④

→ Supervized learning
- Using expert demonstration
- imitation learning: computing the diff between the result of our action and the expert's action (loss function → try to minimize the loss)
- Direct perception: computing the loss on the affordance indicators

→ Reinforcement learning
- learning models based on the loss that we actually care about
  - Minimize time to get to a location
  - Minimize number of collisions

3 types of learning:
- supervized: we have a dataset of samples x_i with labels y_i; we want to learn the mapping $x \to y$
  ex: classification (NNs), regression, imitation learning, affordance learning, etc.
- unsupervized: we have a dataset (x_i) and we want to discover the under-lying structure
  ex: clustering
- Reinforcement learning (RL):
  - agent interacting with an environnement that provides numeric rewards
  - goal: taking actions to maximize the reward
  - ex: learning a manipulation and control tasks.

Q learning est un algo qui va apprendre la valeur d'une action
 −: scalabilité (don't scale to high-dimensional state/action pairs)
 Solution: multi agent RL: split the env. agents collaborate
 et deep Q-learning

(5)

→ Kinematics: geometric description of motion in space
→ Kinetics (or dynamics): describe the laws of the causes of motion

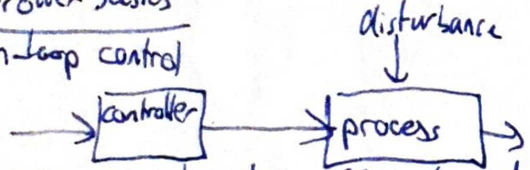
Holonomic constraints
→ constraints position (config) space
→ can freely move in any directions
→ controllable degrees of freedom equal the total degrees of freedom
→ A constraint is defined as $f(x,y,z)=0$
ex: a 3D-particle in which $z=0$

Non holonomic constraints
→ constraint velocity space (i.e. the derivative of position)
→ cannot freely move in any direction
→ controllable degrees of freedom less than the total degrees of freedom
→ constraint cannot be defined as $f(x,y,z)=0$
Example: car

Kinematics of a rigid body
→ A rigid body refers to an infinite collection of small mass points rigidly connected

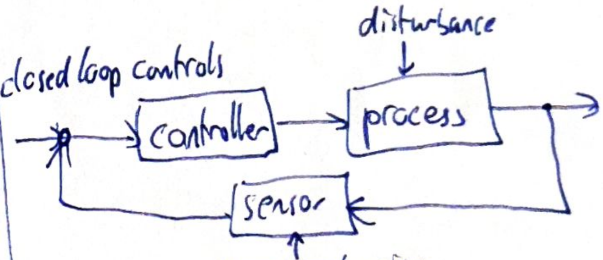
Controller basics

open-loop control



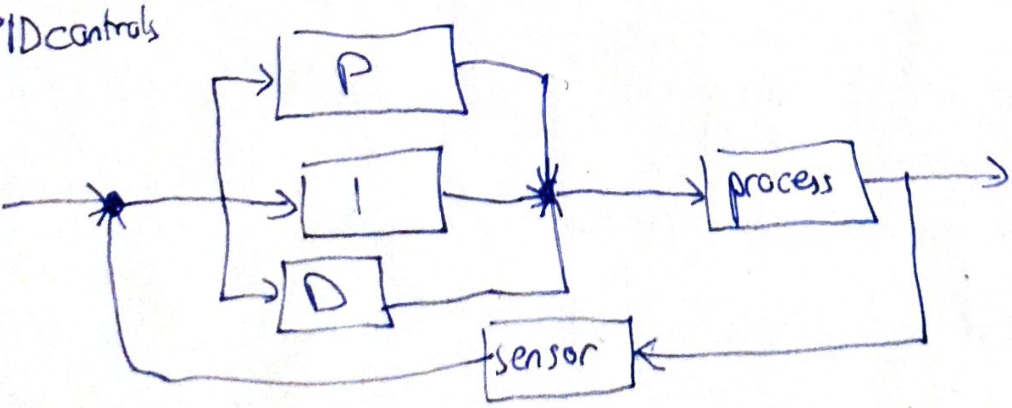
→ require precise knowledge of the plan and the influence factors
→ No feedback about the controlled variable
→ cannot handle unknown disturbance, resulting in drift

closed loop controls



→ exploits feedback to minimize the error between ref and measur
→ this is what is used for controlling a car

PID controls



P: proportional: the P element alone leads to overshooting/oscillation
I: integral: corrects residual errors by integrating past error measurements
D: derivative: alleviates oscillation by introducing a damping behavior