

# Self-driving Car From An Engineering Perspective

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# Outline

Introduction

Safety

AI or Not

System Design Consideration

Motion Planning Design Consideration

Summary



# Introduction

The following are my personal opinions, if you have comments, questions or ideas, please feel free to send me Emails at [cgliu2008 AT gmail.com](mailto:cgliu2008@gmail.com)



# Introduction

People don't believe self-driving car is achievable argue that:

- A computer system is not reliable and safe enough.
- Bugs in software are inevitable.
- A malicious attack can always cause trouble.
- Collisions are inevitable.
- There are a lot of unsolved AI problems, for example, human intent prediction.



# Introduction

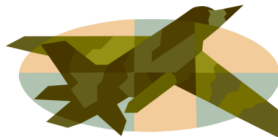
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- There are a lot of unsolved AI problems, for example, human intent prediction.

However, I deeply believe self-driving car is a achievable goal in reasonable near future, here is why and how.

## How to Design A Safety Critical System

**Fly-by-wire Airplane:** There is no mechanical or hydraulic connection between the pilot controls and the control surfaces.



**Drive-by-wire Car:** There is no mechanical or hydraulic connection between the steering wheel and the wheels.



Figure: Examples of safety critical systems

# The $10^{-9}$ Challenge <sup>1</sup>

Critical system services must be more reliable than any one of the components: e.g., System Dependability 1 FIT–Component dependability 1000 FIT (1 FIT: 1 failure in  $10^9$  hours)

- Architecture must be distributed and support fault-tolerance to mask component failures.
- A system as a whole is not testable to the required level of dependability.
- The safety argument is based on a combination of experimental evidence about the expected failure modes and failures rates of fault-containment regions (FCR) and a formal dependability model that depicts the system structure from the point of view of dependability.
- Independence of the FCRs is a critical issue

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<sup>1</sup>From a federated to an integrated architecture for dependable embedded systems, H. Kopetz, TU Wien, September 2004

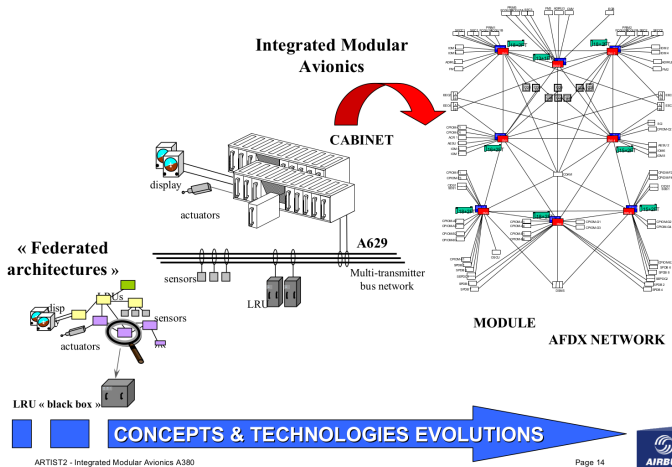
# Independence of FCRs

There are two basic mechanisms that compromise the independence of FCRs

- Missing fault isolation among the FCRs
- Error propagation—the consequences of a fault, the ensuing error, propagates to a healthy FCR by an erroneous message.



# Integrated Architecture



**Figure:** The transition from a federated architecture to an integrated architecture

# Safety Consideration for Integrated Architecture

A number of technical and economic advantages could be realized if the different DASes were integrated into a single architecture

- Cost savings by the reduction of nodes, sensors and wiring points (results also in an increase in hardware reliability).
  - Better integration of functions—more flexibility
  - Implementation of fault tolerance simplified
- But
- Independence of individual DAS compromised—increased potential of error propagation from one DAS to another DAS
  - Integration increases complexity and diagnostics
  - Allocation of responsibility more difficult

# Platform Safety

- DO-297 Integrated Modular Avionics (IMA) Development Guidance and Certification Considerations

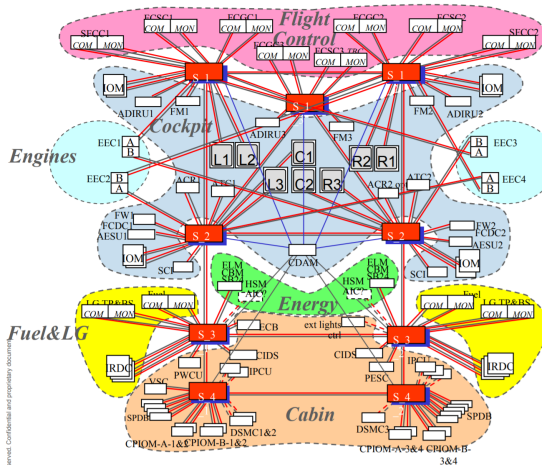
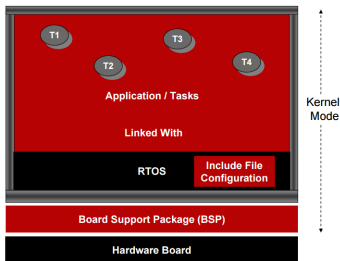


Figure: A380 Integrated Modular Avionics (IMA) system

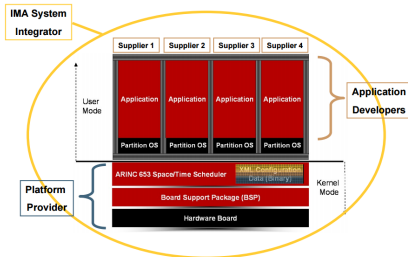
# Platform Safety - OS

- Operating System ARINC 653 (Avionics Application Standard Software Interface) a software specification for space and time partitioning in safety-critical avionics real-time operating systems (RTOS).

## Typical federated system architecture



## VxWorks 653 Architecture



# Platform Safety - Network

- AFDX Avionics Full-Duplex Switched Ethernet (AFDX)
- ARINC 664

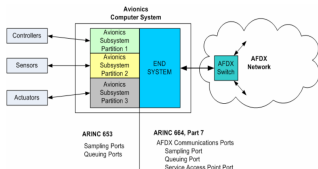
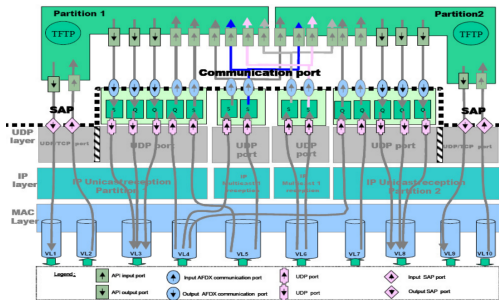


Figure 9. End Systems and Avionics Subsystems Example



# Platform Safety - Software

- Software DO-178B, Software Considerations in Airborne Systems and Equipment Certification

Table A-2 Software Development Processes

	Objective		Activity	Applicability by Software Level				Output		Control Category by Software Level			
	Description	Ref		Ref	A	B	C	D	Data Item	Ref	A	B	C
1	High-level requirements are developed.	5.1.1.a	5.1.2.a 5.1.2.b 5.1.2.c 5.1.2.d 5.1.2.e 5.1.2.f 5.1.2.g 5.1.2.j 5.5.a	○	○	○	○	Software Requirements Data	11.9	①	①	①	①
								Trace Data	11.21	①	①	①	①
2	Derived high-level requirements are defined and provided to the system processes, including the system safety assessment process.	5.1.1.b	5.1.2.h 5.1.2.i	○	○	○	○	Software Requirements Data	11.9	①	①	①	①
3	Software architecture is developed.	5.2.1.a	5.2.2.a 5.2.2.d	○	○	○	○	Design Description	11.10	①	①	①	②
4	Low-level requirements are developed.	5.2.1.a	5.2.2.a 5.2.2.e 5.2.2.f 5.2.2.g 5.2.3.a 5.2.3.b 5.2.4.a 5.2.4.b 5.2.4.c 5.5.b	○	○	○	○	Design Description	11.10	①	①	①	
								Trace Data	11.21	①	①	①	

Figure: DO-178B Software Development Processes Objectives

# Platform Safety - Hardware

- DO-254, Design Assurance Guidance For Airborne Electronic Hardware

Table A-1 Hardware Life Cycle Data by Hardware Design Assurance Level and Hardware Control Category

Data Section	Hardware Life Cycle Data ①	Objectives ②	Submit	Level A	Level B	Level C	Level D
10.1	Hardware Plans						
10.1.1	Plan for Hardware Aspects of Certification	4.1(1,2,3,4)	S	HC1	HC1	HC1	HC1
10.1.2	Hardware Design Plan	4.1(1,2,3,4)		HC2	HC2	HC2	NA
10.1.3	Hardware Validation Plan ③④	4.1(1,2,3,4); 6.1.1(1)		HC2	HC2	HC2	NA
10.1.4	Hardware Verification Plan	4.1(1,2,3,4); 6.2.1(1)	S	HC2	HC2	HC2	HC2
10.1.5	Hardware Configuration Management Plan	4.1(1,2,3,4); 7.1(3)		HC1	HC1	HC2	HC2
10.1.6	Hardware Process Assurance Plan	4.1(1,2,4); 8.1(1,2,3)		HC2	HC2	NA	NA
10.2	Hardware Design Standards						
10.2.1	Requirements Standards ⑤	4.1(2)		HC2	HC2	NA	NA
10.2.2	Hardware Design Standards ⑥	4.1(2)		HC2	HC2	NA	NA
10.2.3	Validation and Verification Standards ⑦	4.1(2)		HC2	HC2	NA	NA
10.2.4	Hardware Archive Standards ⑧	4.1(2); 5.5.1(1); 7.1(1,2)		HC2	HC2	NA	NA
10.3	Hardware Design Data						

Figure: DO-254 Hardware Control Category

# Integrated Modular Self-driving System

- Partitioning system, the performance of each system must be unaffected by any other
  - To allow systems to be developed, tested and verified separately
  - To allow system faults to be contained
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Safety can't be achieved by testing, but by a careful plan, design, implementation, and validation and verification process.

For self-driving cars, it is impractical to follow the same process as what in Aviation for now. But a minimal system engineering effort is still required, which will **save money and time**.

## What are we trying to solve?

Driver-less has already been achieved during the DARPA Robotics Challenges!



Figure: The robot drove a car by itself in the DARPA Robotics Challenge

# What are we trying to solve?



Figure: Tele-assistant system behind the scene



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- Autonomous  $\neq$  Driver-less

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Machine learning methods are good ways to improve performance, but be careful when you decide to use it. They are promising but not magic and the non-interpretative issues with the black-box learning approaches may trap us before achieving acceptable performance. Pure data-driven approaches are expensive and hard to deliver on time.



# What are we trying to solve?

The system design should minimize open 'AI' problems!

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- Have humans in the loop to solve the most challenging AI problem
- Take uncertainties into account during motion planning (robust motion planning)

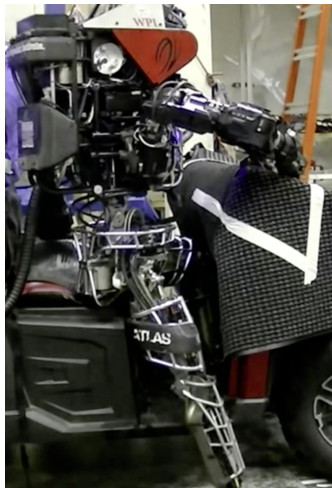
# Lesson Learned from the DARPA Robotics Challenge



- Nimble robots win!
- A hierarchical optimization architecture becomes popular.
- High-speed feedback control (or MPC) is the most efficient way to handle uncertainties and model errors.

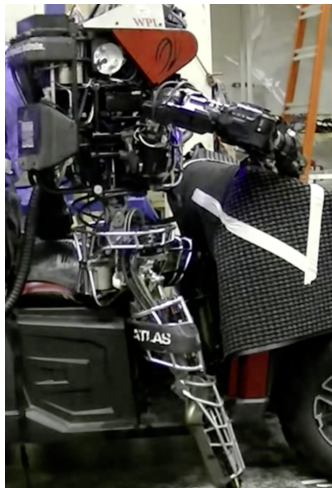


## Lesson learned from the egress task



- Get the robot outside of the car
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High-speed feedback control (or MPC) is critical to the success!

# What makes a system fragile?

- 'Perfectness' assumption. Design a motion planning system assuming that the perception and the prediction system are 'perfect'.

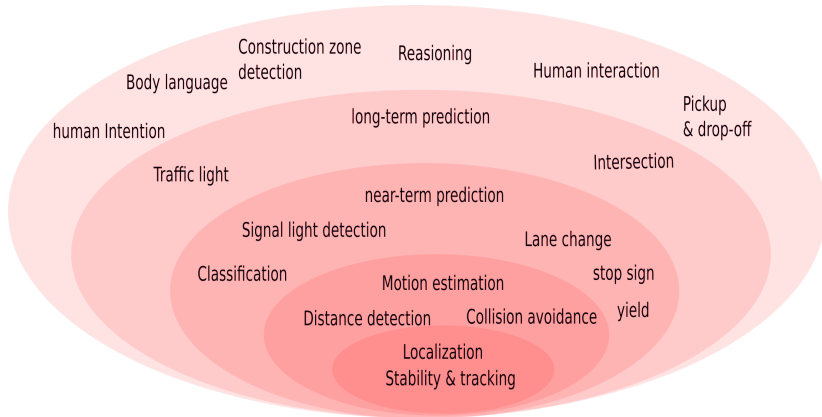
# What makes a system fragile?

- 'Perfectness' assumption. Design a motion planning system assuming that the perception and the prediction system are 'perfect'.
- A death trap
  - To improve the perception system, it runs slower.
  - To improve the prediction system, it runs slower.
  - Because the system runs slower, the motion planning requires a better perception and prediction systems.

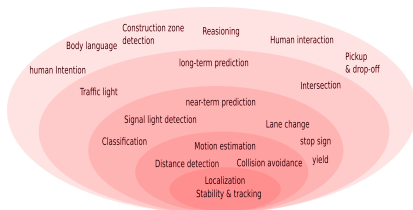
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- A death trap
  - To improve the perception system, it runs slower.
  - To improve the prediction system, it runs slower.
  - Because the system runs slower, the motion planning requires a better perception and prediction systems.
- Handle failure cases separately, case by case. The final system is not consistent.

# Self-driving Architecture

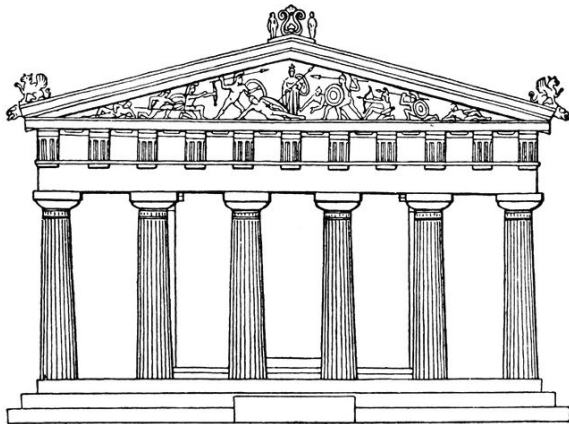


# Self-driving Architecture



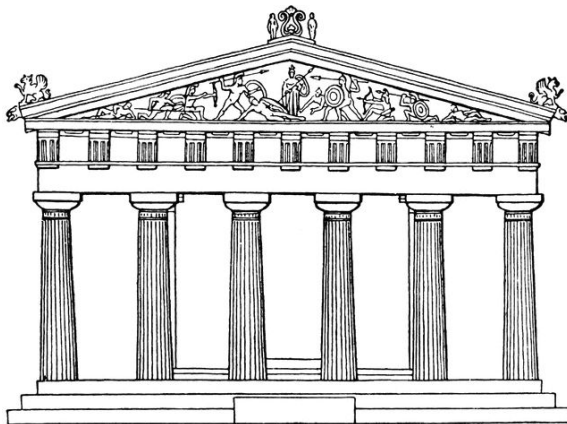
- Each module shall be self-contained and fully functional.
- Each module can be tested, independently.
- The system shall be developed inside-out, not the opposite.
- The response time shall decrease towards the kernel.
- The inner high speed loops are critical to the system robustness.
- The outer modules are important to the system performance (e.g. drive speed) and capabilities (e.g. scenario handling).

# Self-driving Architecture





# Self-driving Architecture



The goal is not a sum of perfect subsystems, but a harmonious system whose parts are consistent with each other!


## Performance goals

When we design a self-driving system, We should consider the system as a whole and optimize its components all altogether.

The following formula show the connects between perception, localization, prediction, and planning systems <sup>2</sup>:

$$\text{clearance} = v_0\tau + \frac{v_0^2}{2a} + 2\sqrt{\sigma_p^2(0) + T^2\sigma_v^2(0)}$$

Divide and conquer, but don't design separately and try to achieve unrealistic goals!

<sup>2</sup><https://cgliu.github.io/posts/self-driving/speed.html> 

## Motion planning system design consideration

- One major reason for self-driving car becoming a realistic goal is that the perception algorithm and systems make a lot of progress in recent years. Compared with the perception system, the motion planning system seems more mature. You probably think it is a solved problem.

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- Therefore, motion planning is NOT a solved problem (exiting!).

The perception system will never be perfect and we can never predict the future. We have to design a motion planning system based on this fact.

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- Yes. according to the analysis <sup>2</sup>, there is always a risk of collision as long as the vehicle moves.

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- However:
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  - And the collision severity levels are different.

Therefore, the design goal is not to avoid all kinds of collisions but to avoid collision in a reasonable way and show **due care** to inevitable collisions or collisions caused by others' faults.

# Motion planning system design consideration

Motion planning system's functionalities:

- Navigation: travel from A to B:
- Guidance: obey traffic law
- Control: avoid collisions

# Optimization-based motion planning

- Rather than designing control policy or rules, the developers design cost functions and then let optimization algorithms figure out the best policy
  - Pros:
    - More direct
    - Easy to get the system to work
    - Make it possible to build a harmonious system
    - Compatible with Reinforcement Learning framework
    - Better performance
  - Cons
    - Hard to find a good cost function
    - Real-time performance issues
    - Robustness issues

# Driving problem formulation

The objectives:

- Minimize the time to the destination
- Minimize the risk of collision
- Maximize ride quality

Subject to:

- Dynamics constraints
- Path, control, and other temporal constraints

# The risk of collision

risk = severity × exposure × probability

The expectation of collision risk:

$$E(\text{risk}) = \int_0^t \text{severity}(\tau) p(\tau) d\tau$$

# The risk of collision

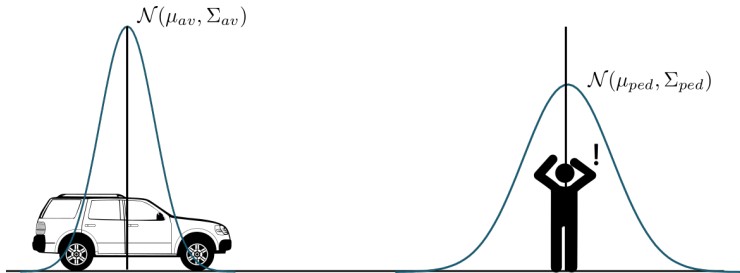


Figure: Probabilistic collision

The collision probability:

$$p(t) \approx \int_S p_{av}(x, y|t) p_{obs}(x, y|t) dx dy$$

# The risk of collision

Figure 2.1: Probability of car driver/passenger fatality by head-on collision (Wrangborg, 2005)

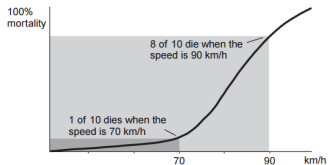
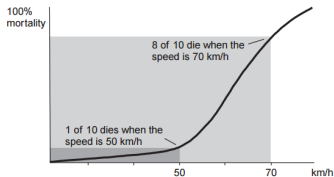


Figure 2.2: Probability of car driver/passenger fatality by side impact collision (Wrangborg, 2005)



# The risk of collision

The severity level at urban drive speed (< 50 mph):

$$\text{severity} \propto v$$

Therefore,

$$E(\text{risk}) \approx \int_0^t \int_S v(\tau) p_{av}(x, y|\tau) p_{obs}(x, y|\tau) dx dy d\tau$$



## Optimal problem formulation

$$U = \arg \min_{u(\cdot)} \left\{ \mathcal{L}_f(x, u, t_f) + \int_{t_0}^{t_f} \mathcal{L}(x, u, t) dt \right\}$$

and subject to:

$$x(0) = x_0$$

$$h(x, u) \leq 0$$

$$E(\text{risk}) \leq \text{risk\_level}$$

The cost functions should take the collision risk, ride quality, the desired driving path and other constraints into account.

# Optimization-based motion planning

- Navigation (long-range)
  - Ignore dynamic obstacles
  - Low resolution, such as at lane level
  - spatial and temporal constraints, e.g. time-based lane
  - Methods: A\*, D\*, PRM, and etc.
- Decision making (long-range and long-term)
  - Simple model, low quality, long-term
  - Method: Dynamic Programming
- Trajectory optimization (mid-range and mid-term)
  - Full model, high quality, mid-term
  - Methods: DDP, iLQR, Direct collocation, Pseudospectral methods, or spline + differential flatness.
- Control
  - Full-model, high quality, short-term
  - Method: Finite-horizon LQR, LQR gain scheduling, QP, ADRC and etc.

# Optimization-based motion planning

- Harmony
  - The cost functions shall be consistent with each other for each level
- Cost functions
  - Manually designed based on domain knowledge
- Real-time performance
  - Cache cost and avoid duplicate computation
  - Hessian matrix approximation,
  - Parallelism (e.g. multiple shooting)
- Robustness
  - Warm-start generation
  - Multiple shooting

# From Excellent to Superb

- Cost function
  - Learning from imitation (Inverse Reinforcement Learning)
    - Maximum Margin Planning
    - Maximum Entropy Inverse Reinforcement Learning
  - Trial and error (Reinforcement Learning, e.g. trajectory-based Reinforcement Learning <sup>3</sup>).
- Real-time performance
  - Cache motion planning priors, similar as use a offline generated library <sup>4, 5</sup>
  - Hierarchical optimization architecture <sup>6</sup>
    - Long-term optimization optimizes for highly-likely, slowly-changing things
    - Short-term optimization optimizes for less-likely, fast-changing things

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<sup>3</sup>Trajectory-based dynamic programming

<sup>4</sup>Standing balance control using a trajectory library

<sup>5</sup>Biped walking control using offline and online optimization

<sup>6</sup>Optimization-based Full Body Control for the DARPA Robotics Challenge



# From Excellent to Superb

- Robustness
  - Reduce latency
  - Plan for uncertainties
    - Hindsight optimization
    - Belief-space planning

# Summary

- System design shall avoid or reduce AI problems
- System development should follow a similar path as the natural evolution. Achieve high-level intelligence based on robust low-level capability, such as lane keeping and collision avoidance.
- Hierarchical optimization architecture is an efficient way to handle real-time performance issues
- Minimizing latency is one of the most efficient ways to improve system robustness.
- Evaluate system safety as a risk probability and design for it
- The motion planning system should consider uncertainty.