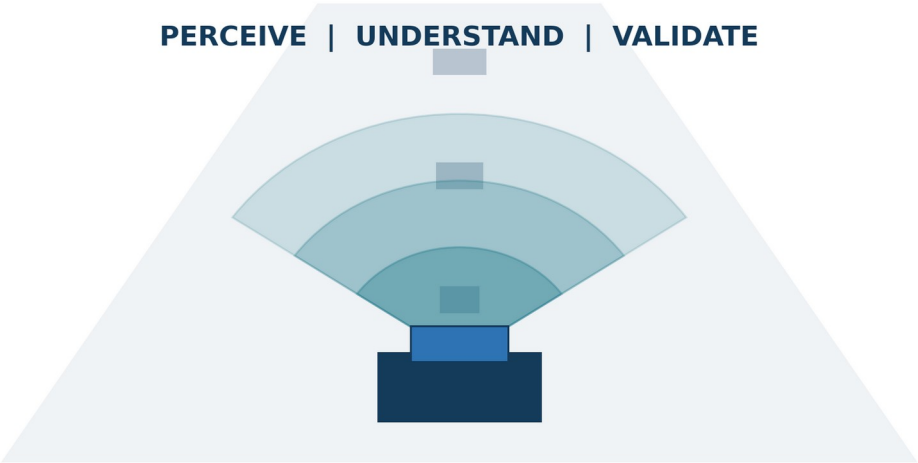
PROJECT DRIVE LEARNING SERIES

ADAS Systems Engineering Theory Handbook

A comprehensive theory companion to the 180-day Project DRIVE course: vehicle systems, sensing, AI, fusion, planning, software, validation, and safety



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Project DRIVE: ADAS Systems Engineering Theory Handbook

Version 1.1 | August 2026

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Technical and safety limitation

This handbook explains engineering concepts; it is not vehicle-specific repair, diagnostic, calibration, legal, or safety authorization. Procedures and specifications vary by year, make, model, option content, software level, market, and repair history. Qualified personnel must use current OEM service information, required tools, applicable regulations, workplace procedures, and appropriate training before performing safety-critical work.

CORE BOUNDARY A scan result, calibration-complete message, or absence of a warning lamp does not by itself prove correct sensor alignment, system performance, or safety. Evidence must be interpreted within the complete vehicle and procedure context.

Author's Note

Modern vehicle safety work sits between two worlds. One world is practical: inspect the vehicle, verify the concern, research the procedure, measure carefully, and document what was done. The other is systems-oriented: understand sensing limits, network dependencies, state estimation, uncertainty, validation evidence, and the boundaries of an operational design domain. I created this handbook to connect those worlds.

The goal is not to turn a reader into a specialist through reading alone. The goal is to build a disciplined mental model that makes training, supervised practice, data review, and vehicle-level testing more productive. Each chapter asks the reader to explain what is known, what remains uncertain, what evidence is needed next, and which decision belongs to the OEM procedure rather than personal assumption.

This handbook is the theory companion to my 180-day Project DRIVE learning structure. Project DRIVE is the systems-engineering learning program. Project VISION is a separate public-safety framework focused on limited ADAS health awareness in periodic inspections. The projects may inform one another, but they are not interchangeable. Neither replaces manufacturer procedures, certification programs, supervised practice, or formal engineering education.

About the author

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How to Use This Book

The 24 chapters follow the theory spine of the 180-day Project DRIVE course: vehicle foundations; sensing, AI, and perception; localization, scene representation, tracking, and fusion; functions, planning, control, and real-time software; then calibration, validation, and safety assurance. Later course phases add Python, Linux, Git, ROS 2, OpenCV, MATLAB/Simulink, CAN tools, packet analysis, simulation, and portfolio projects. This handbook explains the engineering ideas those tools are meant to investigate; it is not a programming manual.

1. Read one chapter for understanding before taking notes. On the second pass, build a one-page system map in your own words.
2. Complete the engineering judgment checks without searching for a single memorized answer. State assumptions and evidence gaps.
3. Use the official ASE Composite Vehicle booklet only where this book directs you to practice reference navigation; do not copy its diagrams into your notes for redistribution.
4. For quantitative exercises, show units and define coordinate frames. A numerically correct value with the wrong frame or unit can still be unsafe.
5. Convert at least four chapters into portfolio evidence: a traceable test plan, a diagnostic decision tree, a sensor-fusion notebook, and a validation report.

The four recurring questions

- What function is expected, and under which conditions?
- Which sensors, modules, networks, vehicle states, and actuators support it?
- What evidence distinguishes normal limitation, configuration issue, physical misalignment, electrical fault, network fault, and algorithmic insufficiency?
- What safe, authorized next action follows from the evidence?

TERMINOLOGY DISCIPLINE ADAS usually describes Level 0-2 driver-support features. SAE Level 3-5 systems are automated driving systems (ADS). This book covers the engineering bridge between them but does not use 'Level 4 ADAS' as a technical synonym for an SAE Level 4 ADS.

What's New in Version 1.1

Version 1.1 expands the handbook from 20 to 24 chapters and strengthens the visual and learning architecture throughout. The new material closes four important theory gaps while preserving the original diagnostic-to-validation perspective.

New theory bridge	What the learner can now explain
Machine learning foundations	Data partitions, leakage, labels, loss, confidence calibration, domain shift, model deployment, and AI assurance
Occupancy and bird's-eye view	Occupied, free, and unknown evidence; inverse sensor models; BEV geometry; dynamic occupancy and spatial validation
Planning and trajectories	Behavior versus motion planning, feasibility, constraints, search, optimization, prediction uncertainty, replanning, and fallback
Real-time software and platforms	Latency, jitter, deadlines, QoS, compute and thermal limits, service-oriented architecture, updates, V2X, and lifecycle traceability

SCOPE PROMISE This is a comprehensive foundation, not a claim that one book can replace OEM training, formal engineering study, standards access, supervised practice, or product-specific validation. The book teaches the complete reasoning chain and the boundaries a responsible engineer must continue to research.

Reference and Originality Policy

The handbook uses a curated reference set: official ASE publications, government and standards-body sources, open-access research, and open-source engineering documentation. Facts, definitions, and public task domains are attributed. The organization, explanations, diagrams, examples, exercises, and decision frameworks in this book are independently written.

Open access does not mean public domain. License terms and author rights still apply. This handbook therefore links readers to source works instead of reproducing their figures, tables, code, or long passages. Where an open-source project is discussed, the project name is used for identification and the reader is directed to its official repository or documentation.

Source class	How it is used	What is not reproduced
ASE public materials	Task-domain alignment and reference-navigation practice	Official questions, diagrams, wiring sheets, logos
Standards and regulators	Terminology, safety scope, public requirements	Paywalled standard text or proprietary figures
Open-access books	Concept checks and recommended further study	Original prose, exercises, or figures from those books
Open-source projects	Architecture examples and hands-on learning routes	Source code or project graphics

Contents

Course chapters and supporting resources

Course resources

PART 1

Vehicle and Systems Foundations

Chapters 1-5

Build the vehicle-level mental model before specializing in any sensor, model, or algorithm.

CHAPTER 01 | PROJECT DRIVE FOUNDATIONS

Engineering Mindset and System Boundaries

Begin with the function, map the complete evidence chain, and resist the urge to diagnose from a single symptom.

Source anchors: R4, R5, R21

LEARNING OBJECTIVES

- Describe an ADAS function as a vehicle-level system rather than a stand-alone sensor.
- Separate observation, interpretation, hypothesis, test, and conclusion in an engineering record.
- Build a functional boundary that includes driver, environment, sensors, networks, controller, actuators, and service state.
- Explain why a plausible explanation is not yet a demonstrated root cause.

From component thinking to function thinking

A forward-collision function does not exist inside a camera or radar alone. It begins with the driving scene and vehicle state, continues through sensing, timing, perception, decision logic, communication, and actuation, and ends with a driver-visible or vehicle-level response. A weakness at any link can change the result. Project DRIVE therefore starts by asking what the vehicle is expected to do, under which conditions, and which dependencies must be healthy before the result can be trusted.

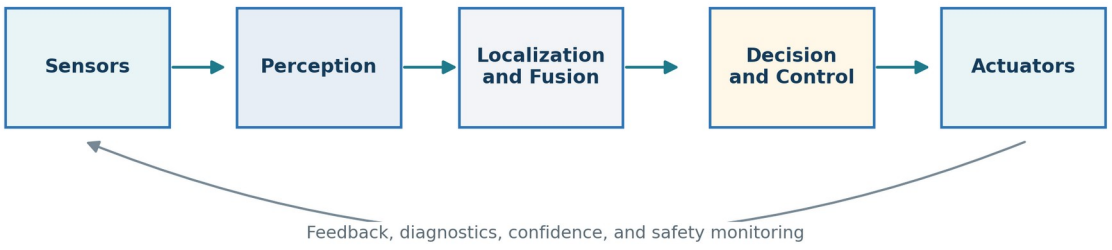


Figure 1.1. Original Project DRIVE system stack: environment and driver context flow through sensing, estimation, decision, control, and vehicle response.

The boundary must be wide enough to include the cause but narrow enough to guide a test. If a lane-support feature is unavailable, a useful first boundary includes road markings, visibility, camera field of view, windshield and mounting condition, camera power and communication, calibration status,

steering and stability-control inputs, driver settings, and enable criteria. It does not begin with the assumption that the camera failed merely because the camera sees the road.

The evidence ladder

Stage	Question	Example
Observation	What was directly seen, measured, or recorded?	Lane icon remained gray during a documented road segment.
Interpretation	What does the observation mean within known logic?	The function did not report an active lane estimate or did not meet enable criteria.
Hypothesis	Which competing causes could explain it?	Marking quality, obstruction, configuration, calibration, network input, or internal fault.
Discriminating test	What evidence separates the hypotheses?	OEM criteria, scan data, image/visibility inspection, geometry records, and controlled road conditions.
Conclusion	Which claim is supported, and what remains open?	Only the cause supported by the complete record; unresolved alternatives stay documented.

Table 1.1. Engineering reasoning keeps raw evidence separate from the story built around it.

PROJECT DRIVE RULE Never promote a hypothesis to a conclusion because it is common, convenient, or consistent with one DTC. Ask what observation would be unlikely if the hypothesis were false.

A DTC, warning lamp, oscilloscope trace, calibration-complete message, or successful road event can be valuable evidence. None is automatically the entire answer. Monitors have thresholds and enabling conditions; scan tools show only the data exposed by a controller; test environments may not exercise boundary cases. Strong records state both what the evidence supports and what it cannot establish.

Requirements, interfaces, and assumptions

A requirement describes behavior that can be checked. Phrases such as 'works correctly' or 'detects cars' are too vague for engineering use. A testable requirement identifies the function, conditions, input or scenario, expected response, tolerance or timing, and evidence to capture. Vehicle programs then decompose that behavior into subsystem and interface requirements while preserving traceability to the original need.

- Inputs: sensor measurements, vehicle state, configuration, driver command, map or external context.
- Outputs: warning, display state, requested torque or deceleration, diagnostic state, logged event.
- Interfaces: signal meaning, unit, scale, range, update rate, timestamp, timeout, validity, and ownership.
- Assumptions: road, weather, target visibility, vehicle loading, tires, alignment, software level, and driver behavior.

- Constraints: latency, compute, power, thermal limits, network capacity, safety mechanisms, and legal boundaries.

Assumptions deserve special attention because they are often invisible until a system leaves the conditions considered during development. A lane model can be mathematically correct yet inappropriate on a construction diversion. A range estimate can be precise yet associated with the wrong object. Engineering judgment is the practice of finding these hidden conditions before they become unqualified claims.

A reusable system-map method

1. Write the function and intended driver benefit in one sentence without naming a component.
2. Define the operating conditions and explicit exclusions known from authoritative information.
3. List physical inputs, electronic inputs, decisions, outputs, feedback, and driver interactions.
4. Draw modules and networks, then annotate signal units, rates, timing, and validity where known.
5. Add physical installation, calibration, configuration, software, and service-history dependencies.
6. Mark every assumption and unknown; convert the highest-risk unknowns into evidence requests or tests.

The map is not a decorative diagram. It is a living reasoning surface. When a test fails, place the observation on the map and trace upstream dependencies and downstream effects. When a change is proposed, use the same map to identify regression risk. When explaining work in an interview, the map demonstrates that you can connect sensor physics, software, networks, controls, and vehicle behavior without pretending that one specialty owns the whole system.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. A vehicle displays 'front assist unavailable' after a windshield replacement. Build four distinct hypothesis classes before selecting a test.
2. Why does a successful scan-tool calibration result not independently prove correct road performance?
3. Rewrite 'the radar is bad' as an observation and an evidence-based diagnostic question.
4. What belongs outside the boundary of an AEB investigation, and how would you justify excluding it?

Answer notes

- Useful classes include environment/visibility, physical installation or geometry, electrical/network/configuration, and module or software behavior. Each class should have evidence that can distinguish it.
- The result establishes only that the tool and controller accepted defined procedural conditions. It may not prove physical setup accuracy, all prerequisites, correct configuration, or performance across the intended scenario space.

- Example: 'The forward radar does not communicate on the expected network during a controlled key state. Which power, ground, network-path, gateway, configuration, or module conditions can explain that observation?'
- Exclude an element only when architecture, requirements, procedure information, or direct evidence shows it cannot affect the observed behavior. Document the basis; convenience is not a boundary rule.

CHAPTER TAKEAWAY Systems engineering begins by preserving the difference between what happened, what it may mean, and what evidence is still required. A disciplined boundary turns complexity into a sequence of testable questions.

CHAPTER 02 | AUTOMATION TAXONOMY

ADAS, ADS, and the Dynamic Driving Task

Use automation terms precisely because responsibility, fallback, and operating boundaries change with the level and feature.

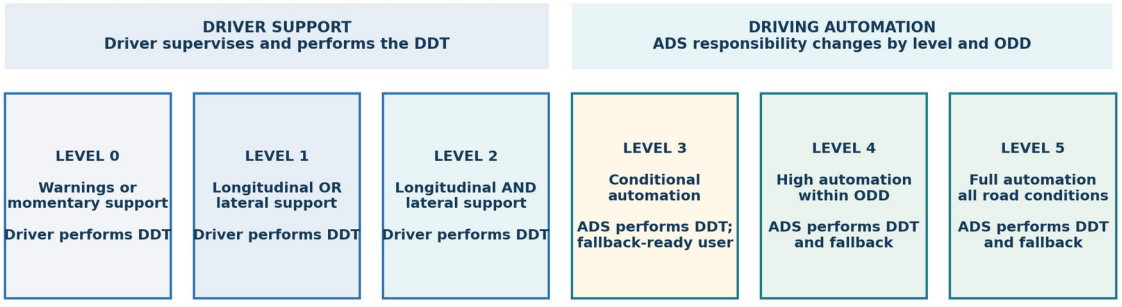
Source anchors: R4, R5, R6, R21

LEARNING OBJECTIVES

- Distinguish driver-support ADAS from an automated driving system.
- Explain the dynamic driving task, fallback, and operational design domain in practical terms.
- Avoid treating an automation level as a measure of sensor quality or marketing sophistication.
- Translate a feature description into responsibility, monitoring, and boundary questions.

Levels describe responsibility, not prestige

Driving-automation taxonomy classifies a feature by the sustained role of the human user and the driving automation system. It is not a star rating, a sensor count, or a claim that every road is supported. A vehicle can contain advanced sensing and still provide Level 2 driver support. Another system may perform the complete dynamic driving task only within a narrow operational design domain. The words must follow the feature behavior, not the vehicle brand or public impression.



Levels describe allocation of the dynamic driving task and fallback - not feature prestige.

Figure 2.1. Original responsibility ladder distinguishing driver support from conditional and higher driving automation.

Category	Driving-task role	Human role	Boundary question
Level 0	Warnings or momentary assistance may occur; the driver performs the driving task.	Continuously drives and supervises.	What does the warning/intervention cover, and what remains entirely with the driver?
Level 1	Sustained lateral or sustained longitudinal support, but not both as an automated combination.	Performs the remaining driving task and supervises.	Which axis is supported, and how is disengagement communicated?
Level 2	Sustained lateral and longitudinal control within feature conditions.	Continuously supervises and remains responsible for the complete driving task.	How are attention, handoff expectations, and feature limits conveyed?
Level 3	ADS performs the complete driving task within its ODD and issues a fallback-ready-user request when needed.	Must be receptive to the request and perform fallback when required.	What triggers the request, and what time and state assumptions support it?
Level 4	ADS performs the complete driving task and fallback within its ODD.	Need not drive while the system operates in its ODD.	How does the system reach a minimum-risk condition when the ODD ends or a fault occurs?
Level 5	ADS performs the complete driving task under all roadway and environmental conditions manageable by a human driver.	No driving role is required.	What evidence justifies the absence of an ODD restriction?

Table 2.1. Compact responsibility view; consult the current SAE taxonomy for formal definitions.

TERMINOLOGY BOUNDARY Project DRIVE uses ADAS for Level 0-2 driver-support functions and ADS for Level 3-5 driving automation. 'Level 4 ADAS' is avoided because it hides the shift in dynamic-driving-task and fallback responsibility.

The dynamic driving task

The dynamic driving task includes operational actions such as steering, braking, accelerating, and monitoring the driving environment, as well as tactical choices such as following, lane selection, responding to objects and events, and planning maneuvers. It does not include every strategic trip decision, such as choosing the destination. For engineers, this distinction creates concrete interfaces: perception describes the scene, prediction estimates likely motion, planning selects behavior and path, and control translates intent into vehicle actuation.

- Lateral vehicle motion control: path and heading through steering or equivalent actuation.
- Longitudinal vehicle motion control: speed and spacing through propulsion and braking.
- Object and event detection and response: observing relevant conditions and acting on them.
- Maneuver planning: choosing actions consistent with route, rules, safety, and surrounding actors.
- Conspicuity actions: lighting, signaling, and other communications where required by the situation.

A feature name rarely proves which parts are automated. 'Highway assist,' for example, may describe different capabilities across products or software revisions. The responsible engineering action is to

locate the authoritative feature description, identify the sustained control role, state who monitors the environment, and define what happens when the feature cannot continue.

ODD, fallback, and minimum-risk condition

An operational design domain describes the conditions in which a driving automation feature is designed to function. It can include road type, mapped area, speed range, traffic, weather, lighting, lane geometry, connectivity, and other constraints. The ODD is not a disclaimer attached after development; it shapes sensing, redundancy, scenario coverage, human interaction, and the fallback strategy from the beginning.

ODD dimension	Example boundary	Evidence needed
Roadway	Controlled-access highway with divided carriageways	Map/road classification, geometry, entrance/exit handling
Environment	No heavy snow or flooded lane markings	Detection/forecast source, thresholds, transition behavior
Speed	Operation only within a defined range	Vehicle-state validity, enforcement, boundary testing
Location	Geofenced service area	Localization integrity, map version, geofence-transition tests
System state	Required sensors, actuators, compute, and communication available	Health monitoring, fault injection, degradation strategy

Table 2.2. An ODD statement becomes useful when each boundary has detection and response evidence.

Fallback is the response when the system cannot continue the dynamic driving task as designed. At Level 3, the system may request a fallback-ready user to take over under defined conditions. At Level 4, the ADS must be capable of achieving a minimum-risk condition within its design scope without depending on a human to complete the fallback. A minimum-risk condition is context dependent: it may be a controlled stop in lane, movement to a shoulder, or another stable condition supported by the system design and environment.

Feature claims that survive scrutiny

1. Name the exact feature and software/configuration context.
2. State the sustained lateral and longitudinal control roles.
3. State who performs object-and-event detection and response.
4. Identify the user role, monitoring expectation, and misuse controls.
5. Define the ODD or operating-condition limits.
6. Describe disengagement, fallback, and minimum-risk behavior without expanding beyond evidence.

This template protects both technical accuracy and public communication. It prevents a demonstration on one clear road from becoming a claim about all roads. It also exposes where validation must

concentrate: boundary detection, transition timing, unusual actor behavior, degraded sensing, and the difference between intended driver support and autonomous responsibility.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. A vehicle steers and controls speed on a highway while requiring continuous driver supervision. What taxonomy evidence matters most?
2. Why can two features with similar names have different automation classifications?
3. Give three testable ODD boundaries for a geofenced Level 4 shuttle.
4. What is technically wrong with describing every advanced driver-assistance feature as autonomous?

Answer notes

- The sustained control of both axes is consistent with Level 2 only when the driver continuously supervises the complete driving task. Marketing terms or sensor sophistication do not change that responsibility allocation.
- Classification follows actual feature behavior: sustained control, environment monitoring, fallback, and operating scope. Names are not standardized capability proofs.
- Examples include mapped-route boundary, maximum speed, precipitation/visibility range, road geometry, connectivity, or required sensor-health state. Each boundary also needs a detection and transition strategy.
- It transfers responsibility that the feature may not hold, obscures driver monitoring, and can hide ODD and performance limitations. Precise language is a safety control.

CHAPTER TAKEAWAY Automation levels describe the allocation of the dynamic driving task and fallback. Precise terms make system boundaries, validation duties, and human responsibility visible.

CHAPTER 03 | VEHICLE STATE AND GEOMETRY

Vehicle Motion, Dynamics, and Coordinate Frames

Every measurement belongs to a frame, time, unit, and motion assumption; lose one and a correct number can become a wrong conclusion.

Source anchors: R13, R19

LEARNING OBJECTIVES

- Define common vehicle, sensor, world, and object coordinate frames.
- Relate speed, acceleration, yaw rate, steering, curvature, and stopping distance without hiding assumptions.
- Explain the purpose of homogeneous transforms and transform chains.
- Recognize where simplified vehicle models are useful and where they fail.

Motion is meaningless without a reference

A target at x = 20 m is not fully described. Is x forward in the radar frame, the vehicle body frame, a map frame, or an image-derived coordinate convention? Was the measurement captured now or transformed from an older timestamp? Coordinate discipline prevents quiet errors when data crosses sensors, ECUs, maps, and analysis tools.

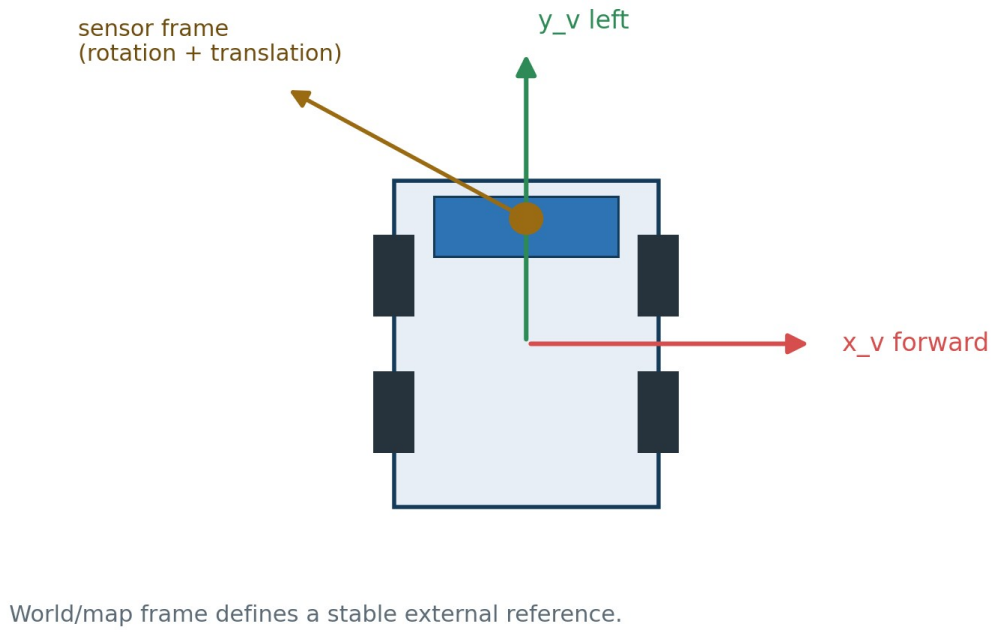


Figure 3.1. Original coordinate-frame example showing vehicle, sensor, and world frames connected by transforms.

Frame	Typical use	Common error
Sensor	Raw range, bearing, pixels, or point coordinates	Treating sensor origin and vehicle origin as identical
Vehicle/body	Ego-relative objects and vehicle dynamics	Changing axis sign or handedness between suppliers
World/map	Localization, trajectories, route geometry	Mixing global and local map projections
Object	Shape, orientation, local motion	Applying vehicle yaw to object orientation without a transform
Image	Pixel location and camera projection	Confusing row/column axes with physical x/y/z

Table 3.1. Frame errors often look like algorithm errors because the numbers remain plausible.

Core kinematic relationships

Kinematics describes motion without requiring a complete force model. It is often the right starting point for state estimation and low-complexity prediction. Dynamics adds the forces, tire behavior, mass distribution, road friction, and actuator limits that explain why motion changes. The simplest acceptable model is the one that preserves the behavior relevant to the decision and declares what it omits.

$$v = dx/dt \qquad a = dv/dt \qquad yaw\_rate = d(heading)/dt$$
$$curvature\ k = 1/R \qquad lateral\_acceleration\ a\_y = v\hat{}2/R = v\hat{}2\ k$$
$$constant\text{-}speed\ TTC = range\ /\ closing\_speed,\ only\ when\ closing\_speed > 0$$
$$idealized\ stopping\ distance\ d = reaction\_distance + v\hat{}2/(2\ |a|)$$

These equations are compact but conditional. Constant-speed time to collision ignores acceleration, turning, target shape, path overlap, and uncertainty. The ideal stopping relation assumes a representative constant deceleration and does not capture brake buildup, grade, tire-road friction variation, actuator delay, or control limits. The engineer uses the formula as a model, labels its assumptions, and checks whether the intended decision is sensitive to them.

Rotation, translation, and transform chains

A rigid transform contains a rotation and translation that map coordinates from one frame to another. Homogeneous coordinates place both operations in one matrix, allowing transform chains to be composed. If a radar reports a point in its local frame, the engineering pipeline may transform it into the vehicle frame and then into a map frame. Order matters: rotating after translating generally produces a different result from translating after rotating.

$$p\_A = R\_AB\ p\_B + t\_AB$$
$$T\_AB = [[R\_AB,\ t\_AB],\ [0\ 0\ 0,\ 1]]$$
$$T\_AC = T\_AB\ T\_BC \qquad T\_BA = inverse(T\_AB)$$

- Name transforms by source and destination, and document the convention.
- Store units and angle conventions with configuration data.
- Validate a transform using known physical points, not only matrix arithmetic.
- Check timestamp alignment before combining a transform with moving measurements.
- Treat calibration uncertainty as part of measurement uncertainty when it matters to the function.

Vehicle models and their boundaries

A kinematic bicycle model combines left and right wheels on each axle into a conceptual pair. At modest lateral acceleration and ordinary tire slip, it provides a useful connection among wheelbase, steering angle, curvature, heading, and vehicle position. It is widely useful for path reasoning and simulation because it is understandable and computationally light. It becomes less accurate near the limits of handling, on low-friction surfaces, during strong transients, or when compliance and tire forces dominate.

MODEL-SELECTION TEST Do not ask whether a model is realistic in every respect. Ask whether its omitted behavior can change the decision, requirement, or safety conclusion being evaluated.

For Project DRIVE work, begin with a transparent model and grow complexity only after a residual, failed scenario, or requirement justifies it. Compare predicted yaw rate and path with measured signals; inspect systematic errors by speed, steering, load, and surface. A model that exposes where it fails teaches more engineering judgment than a black box that fits one dataset without explaining its limits.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. A radar target appears laterally shifted after repair, but range and relative speed look reasonable. Which frame and geometry checks come first?
2. Why can constant-speed TTC be misleading when the lead vehicle is turning out of the ego path?
3. At the same road curvature, what happens to lateral acceleration when speed doubles?
4. When is a kinematic bicycle model inadequate for a validation conclusion?

Answer notes

- Confirm axis conventions, sensor-to-vehicle translation and yaw/pitch/roll, vehicle reference point, calibration configuration, and timestamp. A plausible range does not validate lateral geometry.
- The scalar formula assumes continued closing along a relevant collision path. It ignores lateral separation, path prediction, changing velocity, and object extent.
- Because lateral acceleration is proportional to speed squared, doubling speed produces four times the idealized lateral acceleration at the same radius.
- It is inadequate when omitted tire slip, force saturation, transient response, grade, compliance, or low-friction behavior can affect the requirement or safety decision.

CHAPTER TAKEAWAY Frames, units, timestamps, and assumptions are part of every measurement. Simple models are powerful when their boundaries are visible and dangerous when their convenience is mistaken for truth.

CHAPTER 04 | VEHICLE ELECTRONICS

Electrical/Electronic Architecture and Power Integrity

ADAS software can only be as dependable as the power, grounds, timing, networks, thermal paths, and configuration that sustain it.

Source anchors: R9, R10, R24, R31, R41

LEARNING OBJECTIVES

- Map sensors, domain controllers, gateways, actuators, and driver interfaces in a modern E/E architecture.
- Explain why power integrity and grounding must be evaluated under load and across operating states.
- Distinguish centralized, distributed, domain, and zonal architectural ideas.
- Connect hardware, software, configuration, and thermal state to observed feature behavior.

Architecture is the dependency map

A modern ADAS function can depend on remote sensors, a perception or domain controller, a central gateway, chassis-control modules, driver-monitoring data, instrument-cluster messaging, power-distribution logic, and software configuration. The physical wire diagram shows connections; the functional architecture explains why the connections matter. Both are needed when a feature is unavailable even though each individual module appears to communicate.

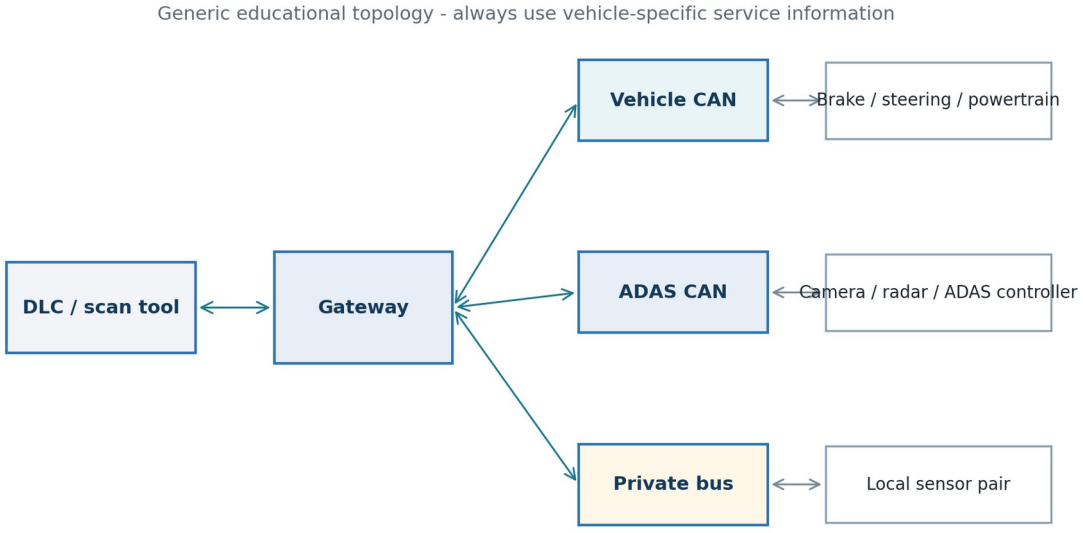


Figure 4.1. Generic original E/E topology with sensors, domain controller, gateway, diagnostics, and chassis networks; it is not a production-vehicle diagram.

Architecture idea	Purpose	Engineering consequence
Distributed ECUs	Functions placed near sensors or actuators	Many interfaces, variants, wake states, and network dependencies
Domain controller	Consolidates compute for a functional domain	Shared-resource, thermal, synchronization, and software-integration concerns
Central compute	Moves major functions to high-performance computers	Higher bandwidth, service-oriented software, mixed criticality, and redundancy needs
Zonal architecture	Groups physical I/O by vehicle area	Gateway/zone-controller routing and power distribution become central dependencies

Table 4.1. Real vehicles may combine several architectural patterns.

Power, ground, wake, and thermal behavior

Open-circuit battery voltage cannot establish that a controller receives acceptable power while booting, transmitting, heating a sensor, or driving an actuator. Voltage drop across feed and ground paths under representative load can reveal resistance that a static continuity test misses. Engineers also consider transient undervoltage, load dump protection, inrush current, sleep current, wake sequencing, and the relationship between ignition state and network availability.

- Measure at the module when possible; a healthy source does not guarantee a healthy delivery path.
- Use a known operating state and appropriate load; intermittent faults may appear only during boot or high activity.
- Evaluate ground offset between interacting modules when analog or communication references matter.
- Document temperature because compute throttling, sensor heating, condensation control, and protection logic can change behavior.
- Preserve connector, terminal-tension, shielding, sealing, routing, and repair-history evidence before disturbing it.

SAFETY BOUNDARY Do not back-probe, load, jumper, or measure an unknown circuit until the authoritative procedure, circuit function, expected range, and safe test method are established. ADAS vehicles may include high-speed, safety-critical, and high-voltage-adjacent circuits.

Compute, software, and configuration

Two physically identical modules may behave differently because their software, parameter set, security state, learned values, or vehicle configuration differ. Replacing hardware can therefore require coding, programming, initialization, calibration, key/security authorization, or a controlled update sequence.

The service record should distinguish these operations; 'programmed and calibrated' is not one undifferentiated step.

Operation	What changes	Evidence question
Programming	Executable software or firmware	Which part/version was installed and did the transfer verify?
Coding/configuration	Variant or feature parameters	Does configuration match vehicle build and authorized option state?
Initialization	Starting references or learned state	Were prerequisites and completion criteria satisfied?
Calibration	Sensor or system relationship to a physical/reference frame	Was the correct procedure, geometry, tool, and environment used?
Adaptation/learning	Values learned through operation	What conditions and duration are required, and how is success evaluated?

Table 4.2. Precise operation names improve traceability and prevent incomplete service claims.

Configuration control also matters in engineering datasets. A regression observed after an update may reflect new logic, a calibration parameter change, a sensor firmware revision, a gateway routing rule, or an incompatible combination. Test reports should capture hardware part numbers, software versions, calibration identifiers, build options, and tool versions so another engineer can reproduce the state.

A structured electrical investigation

1. Confirm the concern, vehicle state, warning history, recent work, and exact function configuration.
2. Research architecture, connector views, grounding, power modes, wake logic, and test precautions.
3. Capture a pre-scan and communication inventory without clearing evidence.
4. Verify power, ground, and network behavior in the operating state that reproduces the concern.
5. Compare commanded state, actual state, validity flags, and relevant signals across module boundaries.
6. After an authorized correction, repeat the same evidence capture and check related functions for regression.

The sequence protects evidence and reduces parts substitution. It also reveals interaction faults: a sensor may be healthy but intentionally disabled because another controller reports invalid steering angle; a camera may boot but miss a required time base; a domain controller may throttle at temperature. Architecture-level thinking makes those possibilities testable instead of mysterious.

Distributed, domain, zonal, and central compute

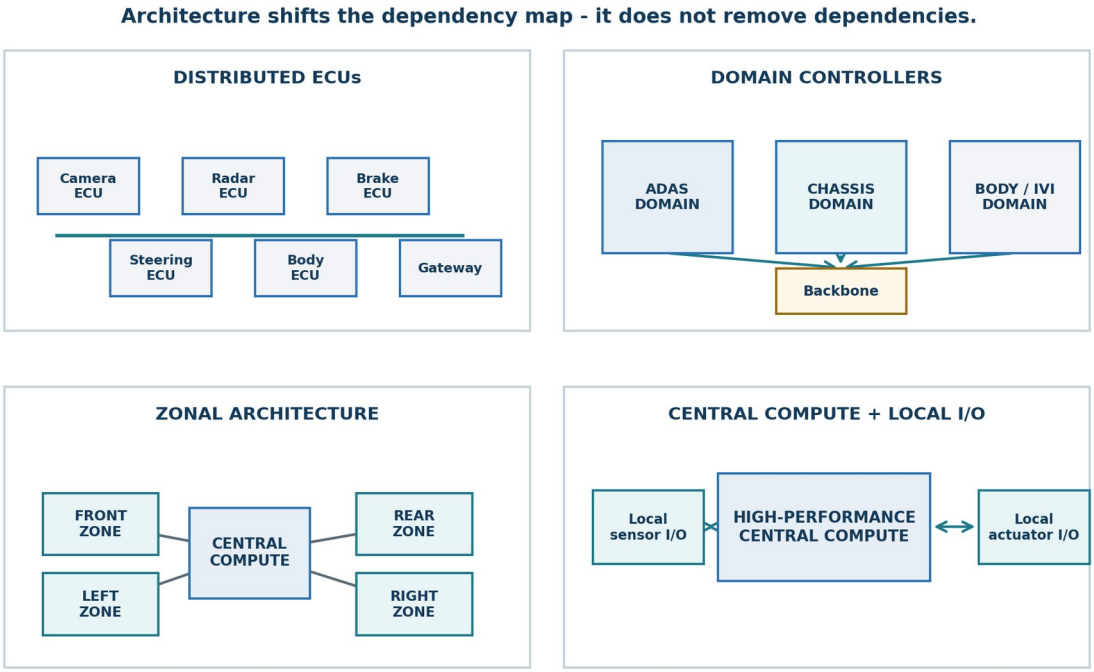


Figure 4.2. Original architecture comparison from distributed ECUs through domain and zonal designs to central compute with local safety I/O.

A distributed architecture places functions across many dedicated ECUs. Domain controllers consolidate related functions such as chassis, body, infotainment, or ADAS. Zonal controllers group physical input and output by vehicle location, while central compute performs larger software workloads. Real vehicles often combine these patterns. Consolidation can reduce wiring and enable shared compute, but it also enlarges shared-failure, thermal, network, cybersecurity, and configuration dependencies.

Service-oriented communication allows applications to discover and use defined services, while signal-oriented communication distributes known values on configured paths. Neither pattern is automatically safer. Engineers must define data ownership, startup order, timeouts, degraded modes, compatibility, and what local control remains available when a central service or backbone link fails.

ARCHITECTURE QUESTION Do not ask only where the ADAS controller is located. Ask which power, network, timing, software, security, cooling, and local-actuation dependencies must remain healthy for the function to behave safely.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. A module shows correct supply voltage unplugged but repeatedly resets when connected. What evidence should be collected next?

2. Why can a software update change the interpretation of an otherwise identical road test?
3. A replacement camera communicates but the feature remains unavailable. List four configuration-state possibilities.
4. How would a zonal architecture change the investigation of several unrelated devices failing in one vehicle corner?

Answer notes

- Measure feed and ground voltage drop during startup/reset, observe current or source stability if authorized, inspect terminals and shared paths, and correlate reset timing with network and thermal state.
- Algorithms, thresholds, message timing, diagnostics, calibration values, or feature logic may have changed. Version and configuration are therefore test conditions, not administrative details.
- Possible states include missing coding, incompatible software, incomplete initialization, required physical calibration not performed, security authorization incomplete, or learned values not established.
- A shared zone controller, local power distribution, gateway route, connector, or harness segment becomes a common-cause candidate. The architecture narrows the shared dependencies before component replacement.

CHAPTER TAKEAWAY E/E architecture links physical power and communication to software state and vehicle behavior. Diagnose the operating system around the ECU, not merely the ECU label.

CHAPTER 05 | COMMUNICATION AND DIAGNOSTICS

CAN, CAN FD, Gateways, UDS, DoIP, and Automotive Ethernet

A network trace becomes useful only when physical integrity, protocol behavior, signal meaning, timing, and diagnostic context are interpreted together.

Source anchors: R9, R10, R18, R24

LEARNING OBJECTIVES

- Explain arbitration, framing, error handling, and termination at a practical systems level.
- Distinguish network transport from application-signal meaning and diagnostic services.
- Describe the roles of CAN FD, Automotive Ethernet, gateways, UDS, and DoIP.
- Build a non-destructive evidence sequence for communication concerns.

From voltage to vehicle meaning

At the physical layer, the engineer asks whether voltage levels, wiring, termination, shielding, topology, and transceiver behavior support communication. At the data-link layer, the questions involve identifiers, arbitration, frames, errors, and timing. At the application layer, bytes become signals with scale, offset, unit, validity, counters, and state definitions. A clean-looking waveform does not prove correct signal meaning, and a correct decoded signal does not prove every physical margin is healthy.

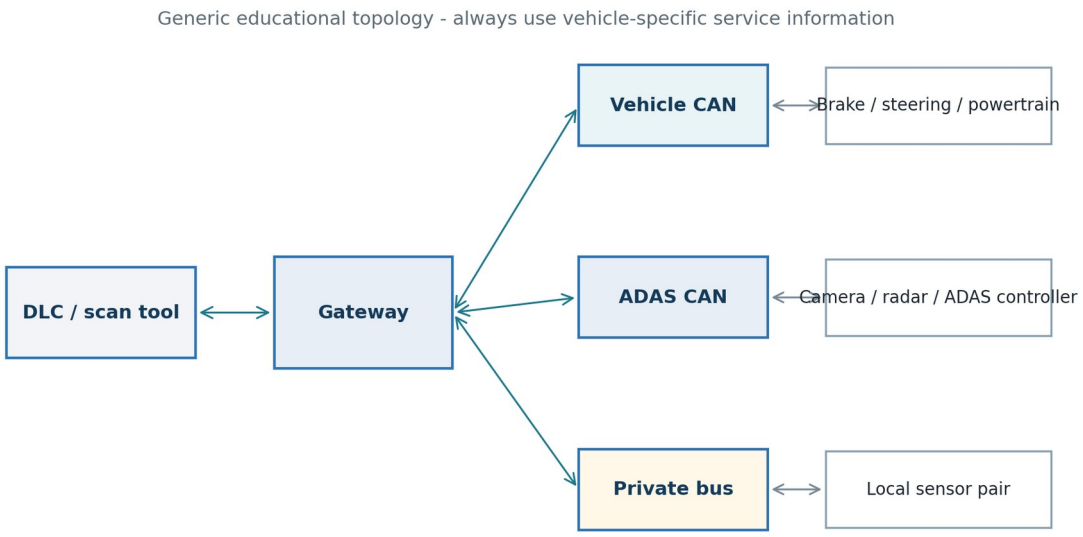


Figure 5.1. Generic multi-network vehicle architecture for reasoning about routing, diagnostics, and shared dependencies.

Layer	Typical evidence	Misleading shortcut
Physical	Loaded voltages, differential waveform, resistance/topology, connector condition	A continuity beep proves the network
Data link	Frame IDs, rates, error frames, bus load, missing or duplicated traffic	Any traffic means every node is healthy
Application	Decoded value, unit, validity, counter, timeout, plausibility	A changing byte has the assumed meaning
Diagnostic	Session, service, response code, DTC status, snapshot, security/access state	One scan-tool label is the root cause

Table 5.1. Network evidence should be labeled by layer before conclusions are drawn.

CAN and CAN FD behavior

Classical CAN is a message-oriented, multi-master bus. Nodes transmit identifiers that participate in non-destructive bitwise arbitration; the numerically lower identifier wins when competing frames begin together under standard conventions. The identifier describes message priority and meaning through network design, not the physical address of a sender in the ordinary point-to-point sense. Error detection and fault confinement help prevent one unhealthy node from indefinitely corrupting the bus.

CAN FD extends payload capacity and can use a faster data phase after arbitration. It improves efficiency for larger transfers but does not remove physical-layer limits. Cable length, topology, transceiver capability, termination, and signal integrity remain important, especially as bit rate increases. Engineers must know whether a capture tool, interface, and decoder support the actual network mode before interpreting missing data as a vehicle fault.

- Measure resistance only with the network safely powered down and according to approved procedures; parallel modules and topology affect the result.
- A nominal approximately 60-ohm reading is a common two-terminator concept, not a universal rule for every vehicle network.
- Use differential and individual-line behavior together when diagnosing opens, shorts, bias faults, or common-mode problems.
- Correlate error frames, bus load, missing messages, and module resets with the reported function concern.
- Preserve timestamps and capture configuration so traces can be compared after a change.

Gateways, Ethernet, and time

A gateway may route, filter, translate, secure, or reshape traffic among networks. Therefore, a module can be healthy on its local segment while appearing absent from diagnostic access, or a remote signal can be stale even though the receiving controller still communicates. A gateway investigation

distinguishes local-network presence, route configuration, source freshness, destination timeout behavior, and cybersecurity authorization.

Automotive Ethernet supports higher bandwidth and switched point-to-point communication useful for cameras, centralized compute, diagnostics, and service-oriented systems. Engineers encounter MAC and IP addressing, switching, VLANs, packet timing, time synchronization, and higher-layer protocols. Ethernet does not automatically make data real-time or synchronized; latency, queuing, clock alignment, packet loss, and application scheduling must be measured against the function requirement.

TIMESTAMP QUESTION The arrival time at a logger is not necessarily the sensor exposure or measurement time. Record which clock created the timestamp, how clocks are synchronized, and where buffering or gateway delay can occur.

UDS and DoIP as diagnostic conversations

Unified Diagnostic Services provides standardized service concepts such as session control, data reading, DTC information, routine control, security access, communication control, and programming transfer. Vehicle implementations define which services, data identifiers, sessions, timings, and access conditions are available. A negative response is information: it can indicate an unsupported service, incorrect sequence, unmet condition, timing issue, or denied access rather than a failed ECU.

Diagnostics over Internet Protocol carries diagnostic communication over IP-based vehicle networks. It can support faster data transfer and access to Ethernet-connected architecture, but the diagnostic service semantics still require correct sessions, addressing, routing, and authorization. Test tools must be configured for the vehicle and task; unauthorized attempts to bypass access controls are outside responsible Project DRIVE practice.

1. Capture the concern, key state, wake state, battery support, and network inventory.
2. Use current topology and service information to identify the expected path from tool to target ECU.
3. Separate no communication, negative diagnostic response, invalid application signal, and feature-level unavailability.
4. Check local power/ground and local-segment traffic before condemning a gateway or remote module.
5. Correlate timestamps, DTC status, snapshots, counters, and message timeouts across interacting modules.
6. After correction, repeat the same capture and verify both communication and the vehicle function.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. A scan tool cannot reach one ECU, but other modules report lost communication with it. What does that evidence suggest, and what does it not prove?

2. Why is a steady decoded value not automatically a stuck sensor?
3. A CAN trace shows traffic but a function reports stale vehicle speed. Which layers must be checked?
4. What additional evidence is required before interpreting a negative UDS response as an ECU fault?

Answer notes

- The ECU may be offline or unreachable on its local power/network path, but the result does not isolate module failure from power, ground, wiring, wake, local bus, gateway route, or configuration.
- The physical quantity may be steady, the signal may update with the same value, a gateway may repeat cached data, a validity flag may be false, or the decoder definition may be wrong. Check counters, timestamps, raw traffic, source, and context.
- Verify physical integrity, frame presence/rate/error behavior, correct decoding and validity, gateway routing/freshness, receiving timeout logic, and the function's use of the signal.
- Identify the requested service and session, response code, addressing, preconditions, timing, security state, supported implementation, and whether the tool sequence matches authoritative information.

CHAPTER TAKEAWAY Vehicle communication diagnosis moves from physical evidence to protocol behavior to signal meaning and finally function impact. Never collapse those layers into a single 'network good' or 'network bad' judgment.

PART 2

Sensing, AI, and Perception

Chapters 6-11

Understand what sensors measure, how learned and geometric perception infer scene structure, and where uncertainty begins.

CHAPTER 06 | SENSING AND PERCEPTION

Camera Systems and Image Formation

A camera measures light projected through optics; everything called an object, lane, sign, or free-space boundary is an inference built afterward.

Source anchors: R4, R17, R26

LEARNING OBJECTIVES

- Explain the camera imaging chain from scene illumination to a digital image and perception output.
- Distinguish intrinsic calibration, extrinsic calibration, mounting geometry, and software interpretation.
- Relate resolution, field of view, exposure, dynamic range, distortion, and motion blur to feature performance.
- Separate normal visual limitations from physical, electrical, configuration, calibration, and algorithm concerns.

What the camera actually measures

A camera begins with photons reflected or emitted by the scene. Lenses direct that light onto an image sensor, where exposure and gain help convert it into digital intensity and color information. Image-signal processing may correct color, noise, lens shading, and dynamic range before perception software estimates lanes, signs, vehicles, pedestrians, or free space. Every stage introduces assumptions and possible information loss.

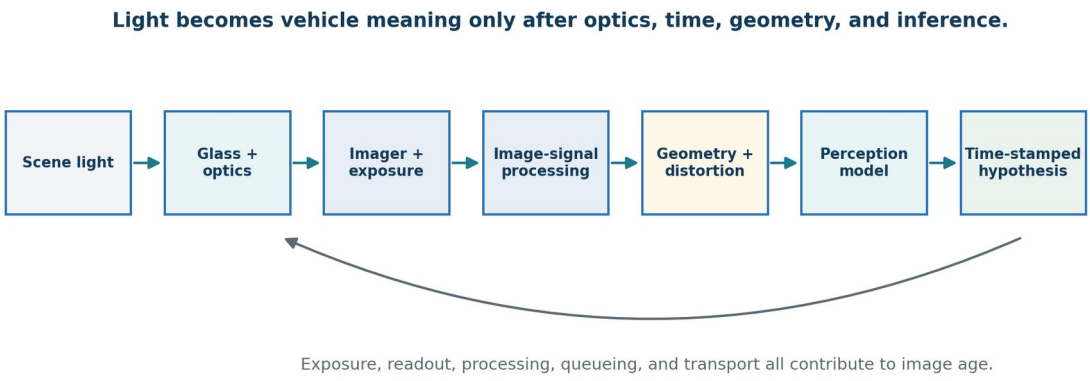


Figure 6.1. Original camera chain from scene illumination and optics through exposure, image-signal processing, geometric correction, perception, and time-aligned output.

Imaging element	Engineering tradeoff	Possible symptom
Field of view	Wide coverage versus pixels per angular degree and distortion	Distant detail is too small or edge geometry is distorted
Resolution	Spatial detail versus bandwidth, compute, and low-light noise	Small targets or lane markings occupy too few reliable pixels
Exposure/gain	Visibility in dark regions versus saturation, noise, and blur	Headlights clip while shadow objects disappear
Dynamic range	Ability to preserve bright and dark information together	Tunnel exit, low sun, or reflective road hides structure
Frame rate	Temporal detail versus exposure time, bandwidth, and compute	Fast lateral motion changes substantially between frames
Optics/window	Focus and transmission versus packaging and contamination	Blur, flare, haze, obstruction, or local contrast loss

Table 6.1. Camera performance is a chain of coupled optical, electronic, and computational choices.

Image quality cannot be reduced to sharpness alone. A sharp raindrop on the windshield can obscure the road; aggressive denoising can erase a faint lane; high gain can reveal an object while increasing false texture. The relevant question is whether the retained image information supports the intended perception task under specified conditions.

Projection and camera calibration

The pinhole model describes how a three-dimensional point projects to a two-dimensional image. Focal lengths and the principal point are intrinsic parameters; distortion coefficients describe deviations introduced by the lens. Extrinsic parameters describe the camera's rotation and translation relative to a vehicle or world reference. Vehicle service calibration commonly addresses the installed relationship of the camera and vehicle, while intrinsic parameters are usually established by the camera design and manufacturing process.

$$u = f_x\,(X/Z) + c_x \qquad v = f_y\,(Y/Z) + c_y$$

$$p_{image} \sim K\,[R \mid t]\,p_{world}$$

$$\text{angular\_error creates lateral\_error approximately equal to range x angle for small angles}$$

Projection loses depth: many world points can lie on the same image ray. Monocular depth must therefore use learned scene cues, object size assumptions, road geometry, motion over time, or fusion with other sensors. A small pitch error can move the estimated road horizon and create large distance error far ahead. That is why vehicle attitude, ride height, tires, loading, alignment, windshield/camera mounting, and target geometry may matter to a vehicle-specific calibration procedure.

CALIBRATION BOUNDARY Do not infer a universal camera-calibration trigger or setup. Research the exact year, model, option, sensor, software state, repair, and procedure. Static, dynamic, and combined processes are not interchangeable labels.

Environmental and scene limitations

Camera limitations often occur when the scene does not provide stable visual contrast or resembles something outside the model's experience. Low sun, glare, darkness, fog, spray, snow cover, worn markings, unusual vehicles, shadows, construction patterns, and lens obstruction can reduce confidence without an electrical fault. A responsible investigation first determines whether the condition is within documented feature capability and whether the limitation is repeatable under controlled, safe conditions.

Evidence class	Questions
Environment	Lighting direction, contrast, precipitation, road marking quality, target visibility, construction state?
Optical path	Glass type/condition, tint or coating, contamination, condensation, glare, damage, obstruction?
Physical installation	Bracket, fastener, seating, sensor aim, windshield replacement, body geometry, vibration?
Electrical/data	Power, temperature, communication, timestamps, image availability, validity, DTC context?
Configuration/calibration	Correct part and software, coding, initialization, current procedure, prerequisite evidence?
Algorithm/feature	Enable criteria, confidence, scene category, expected limits, repeatability, software revision?

Table 6.2. A camera concern should be classified before parts or calibration are proposed.

Project DRIVE camera study method

1. Define one camera-supported function and the image information it requires.
2. List expected environmental limits and vehicle prerequisites from authoritative sources.
3. Trace the imaging chain: optical path, sensor, image processing, perception, fusion, decision, display or actuation.
4. Create a condition matrix varying lighting, contrast, motion, obstruction, and marking quality without unsafe road experimentation.
5. For each observation, distinguish raw-image limitation, projection/geometry issue, perception uncertainty, and feature logic.
6. Record the test configuration and avoid claiming a vehicle-wide conclusion from one scene.

In later Project DRIVE phases, the same method becomes an OpenCV or dataset exercise. Inspect histograms, edges, blur, perspective, and regions of interest, then compare how a simple algorithm changes across conditions. The objective is not to create a production perception stack; it is to learn why controlled data, labeled assumptions, and negative cases matter.

Temporal imaging, rolling shutter, and multi-view depth

An image is not always captured at one instant. A rolling-shutter sensor exposes rows at slightly different times, so fast motion, vibration, or rapid yaw can distort geometry. Motion blur integrates light during exposure, while frame latency includes exposure, readout, image processing, transport, and perception. A feature reported with the wrong effective timestamp can be spatially wrong even when the pixels look sharp.

Stereo cameras estimate depth from disparity between synchronized views with a known baseline. Multi-camera systems can extend coverage or create surround views, but require overlap, extrinsic calibration, synchronized capture, and consistent exposure behavior. Optical flow estimates apparent image motion and can support ego-motion or actor-motion reasoning, yet depth, rotation, texture, and occlusion make interpretation ambiguous. These methods add evidence; they do not remove the need for geometry and uncertainty.

Temporal effect	Observable symptom	Evidence to inspect
Rolling shutter	Slanted or warped moving structure	Row timing, motion/yaw rate, exposure, sensor mode
Motion blur	Edges spread along motion direction	Exposure time, speed, vibration, lighting, gain
Frame latency	Correct detection at an old position	Capture timestamp, pipeline stages, queue age
Stereo mismatch	Unstable or missing depth	Synchronization, baseline/extrinsics, texture, occlusion

Table 6.3. Camera timing can become a geometry error.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. A lane detector performs well at noon but fails near sunset on the same road. Build an evidence plan before proposing recalibration.
2. Why can a one-degree mounting-angle error become more important at long range?
3. A replacement windshield is optically clear. What additional camera-system questions remain?
4. Why does higher image resolution not guarantee better object detection?

Answer notes

- Document illumination direction, glare, exposure/saturation, shadow contrast, lens/window condition, marking visibility, feature limits, raw-data availability, and repeatability. Compare controlled conditions before treating geometry as the cause.
- For small angles, lateral or vertical displacement grows approximately with range times angle. A modest angular bias can therefore shift distant projections substantially.
- Correct glass specification, bracket location and stability, camera seating, coatings/tint, distortion, required initialization or calibration, body/alignment state, software/configuration, and OEM procedure applicability.
- More pixels increase bandwidth and compute and may add noise; task performance also depends on optics, exposure, training data, model design, target scale, contrast, timing, and calibration.

CHAPTER TAKEAWAY Camera output is a structured inference from light. Diagnose the full imaging and geometry chain, and treat scene limitations as test conditions rather than automatic evidence of component failure.

CHAPTER 07 | SENSING AND PERCEPTION

Radar Systems and Relative Motion

Radar is strong at range and radial motion, but reflections, geometry, resolution, and association determine whether a return becomes the right object.

Source anchors: R4, R12, R20

LEARNING OBJECTIVES

- Explain range, azimuth, elevation, radial velocity, and radar cross-section at a working level.
- Describe how frequency-modulated continuous-wave radar estimates range and relative speed conceptually.
- Recognize multipath, ghost targets, clutter, occlusion, resolution, and alignment limits.
- Connect radar measurements to tracking, fusion, calibration, and service evidence.

What radar contributes

Automotive radar transmits electromagnetic waves and analyzes returns from objects and surfaces. It can provide range and radial relative velocity directly, with angular information determined by antenna arrangement and signal processing. Because radio wavelengths and reflection behavior differ from visible light, radar can remain useful in some darkness, glare, or weather conditions that challenge cameras. It is not weather-proof or ambiguity-free.

Measurement	Meaning	Important limitation
Range	Distance along the measured path	Resolution and multipath can merge or displace returns
Azimuth/elevation	Direction relative to the radar frame	Angular resolution and mounting bias affect lateral placement
Radial velocity	Closing or opening component along the line of sight	Lateral motion can have little radial component
Return strength	Received energy related to target and geometry	Not a simple object-size measurement; angle and material matter
Detection/cluster	Processed grouping of radar energy	Not yet a stable object identity or classification

Table 7.1. Radar measurement dimensions become vehicle meaning only after geometry and tracking.

FMCW concepts without hidden magic

Many automotive radars use frequency-modulated continuous-wave chirps. The transmitted frequency changes over a known interval. Mixing the received echo with the transmitted signal produces beat information related to propagation delay and therefore range. Comparing phase or frequency behavior

across chirps can reveal Doppler-related radial velocity. Multiple receiving elements provide phase differences used to estimate direction.

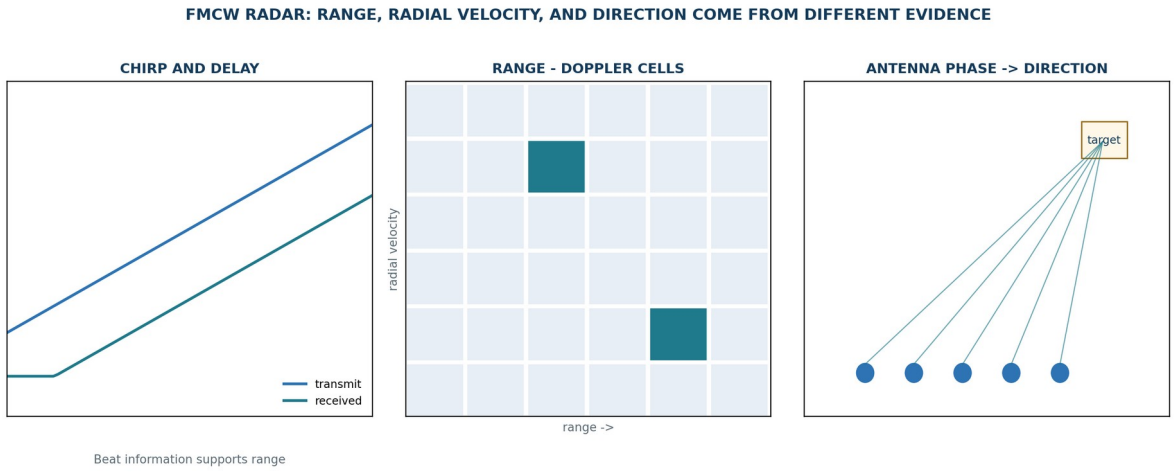


Figure 7.1. Original FMCW radar concept showing chirps, beat information, Doppler across chirps, and antenna phase for range, radial velocity, and direction.

$$\text{range is proportional to beat\_frequency / chirp\_slope}$$
$$\text{radial\_velocity is proportional to Doppler\_shift x wavelength}$$
$$\text{measured radial speed} = \text{relative\_velocity dot line\_of\_sight\_unit\_vector}$$

Real processing separates multiple targets, suppresses interference, estimates angles, clusters points, and manages ambiguous combinations. Range resolution depends on waveform bandwidth; velocity resolution depends on observation structure and duration; angular resolution depends on aperture and processing. These tradeoffs interact with update rate, compute, packaging, and regulatory constraints. Project DRIVE uses these relationships to interpret outputs, not to infer proprietary radar design parameters.

Reflection, geometry, and false structure

A radar return depends on target material, shape, orientation, frequency, polarization, distance, and surroundings. Metal structures can create strong reflections; smooth surfaces can redirect energy; guardrails and large signs can generate persistent clutter. Multipath occurs when energy follows more than one route, potentially creating a ghost location or misleading range. Occlusion can hide a smaller target behind a stronger reflector.

- A stationary object can matter even when Doppler filtering makes it harder to separate from background.
- A cross-traffic object can have strong lateral motion but a small radial speed until geometry changes.
- Two close objects may merge when separation is below range or angular resolution.

- A large return is not automatically the most collision-relevant object.
- Track history and camera/lidar context can help, but fusion can also spread a bad association.

SCENARIO INSIGHT When a radar output appears wrong, ask whether the measurement is physically plausible for a different reflection path or object before assuming random sensor failure.

Alignment, installation, and verification

Radar angle is expressed in the radar frame. If the installed sensor is rotated relative to the vehicle reference, every target direction can inherit a bias. A bracket may look undamaged yet be shifted; a fascia may affect transmission; vehicle ride height or thrust direction can change the relationship between sensor and road. Vehicle-specific procedure research determines whether inspection, measurement, calibration, programming, or dynamic learning is required.

1. Confirm part, mounting, bracket, fasteners, fascia/radome condition, and repair history without disturbing evidence.
2. Research the current OEM prerequisites, vehicle reference, tools, environment, and completion criteria.
3. Document tires, ride height/loading, alignment or thrust-line state when the procedure makes them relevant.
4. Verify power, communication, temperature state, software/configuration, and diagnostic context.
5. Perform only the authorized calibration or initialization and retain setup and result records.
6. Complete the prescribed post-procedure checks; a road event must be safe, legal, repeatable, and within documented conditions.

Resolution, virtual apertures, and interference

Range resolution depends strongly on swept bandwidth; velocity resolution depends on the observation across chirps; angular resolution depends on effective aperture and signal processing. Multiple transmit and receive channels can form a virtual array that improves angular information without one physically continuous antenna. Resolution remains different from accuracy: two objects may be separable yet each estimate can still be biased, and an accurate mean can hide poor ability to resolve adjacent actors.

Other radars, reflections from the vehicle body, bumper material, water or ice, and electromagnetic interference can raise noise or create structured artifacts. Interference mitigation, waveform scheduling, filtering, and plausibility checks are part of the design. Service changes to fascia, brackets, radomes, paint, or accessories can alter transmission and reflection even when no external damage is obvious.

RESOLUTION BOUNDARY Do not use range, velocity, and angle resolution interchangeably. A radar can separate two speeds but merge two angles, or place a strong reflector accurately while missing a weak nearby actor.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. A target has near-zero radial velocity but is moving quickly across the vehicle's path. Explain the geometry.
2. Why can a secure radar bracket still create a vehicle-level alignment concern?
3. A radar reports a strong object near a guardrail. What competing interpretations should a tracker or investigator consider?
4. Why is return strength alone a poor object-classification rule?

Answer notes

- Radar measures the component of relative velocity along its line of sight. Motion nearly perpendicular to that line can produce little Doppler until the relative geometry changes.
- Secure only describes fastening. The bracket or mounting surface may be geometrically shifted relative to the vehicle reference, thrust line, or designed sensor pose.
- A real vehicle, guardrail cluster, multipath ghost, merged targets, or temporary association error are plausible. Check spatial consistency, radial motion, history, ego path, other sensors, and scene geometry.
- Radar cross-section changes with material, shape, orientation, distance, and frequency. Different objects can produce similar strength, and the same object can vary dramatically with angle.

CHAPTER TAKEAWAY Radar provides valuable range and radial-motion evidence, not automatic object truth. Geometry, reflection physics, alignment, and temporal association determine how that evidence should influence a function.

CHAPTER 08 | SENSING AND PERCEPTION

LiDAR, Ultrasonic, and Short-Range Sensing

Different ranging sensors fail differently; their value comes from complementary evidence, not from a claim that one sensor is universally best.

Source anchors: R4, R15, R16

LEARNING OBJECTIVES

- Describe time-of-flight LiDAR and ultrasonic ranging concepts.
- Interpret point clouds, scan patterns, range limits, reflectivity, and short-range coverage.
- Compare sensing modalities by measurement, uncertainty, environment, packaging, and function role.
- Identify realistic contamination, surface, multipath, cross-talk, occlusion, and installation concerns.

LiDAR as sampled three-dimensional geometry

LiDAR emits light and estimates distance from the returned energy, commonly using time of flight or another ranging method. Repeating the measurement across directions produces a point cloud containing coordinates and often intensity or timing information. The pattern is sparse relative to the continuous world. Surface orientation, reflectivity, beam divergence, weather, motion, scan timing, and occlusion determine which parts of an object appear.

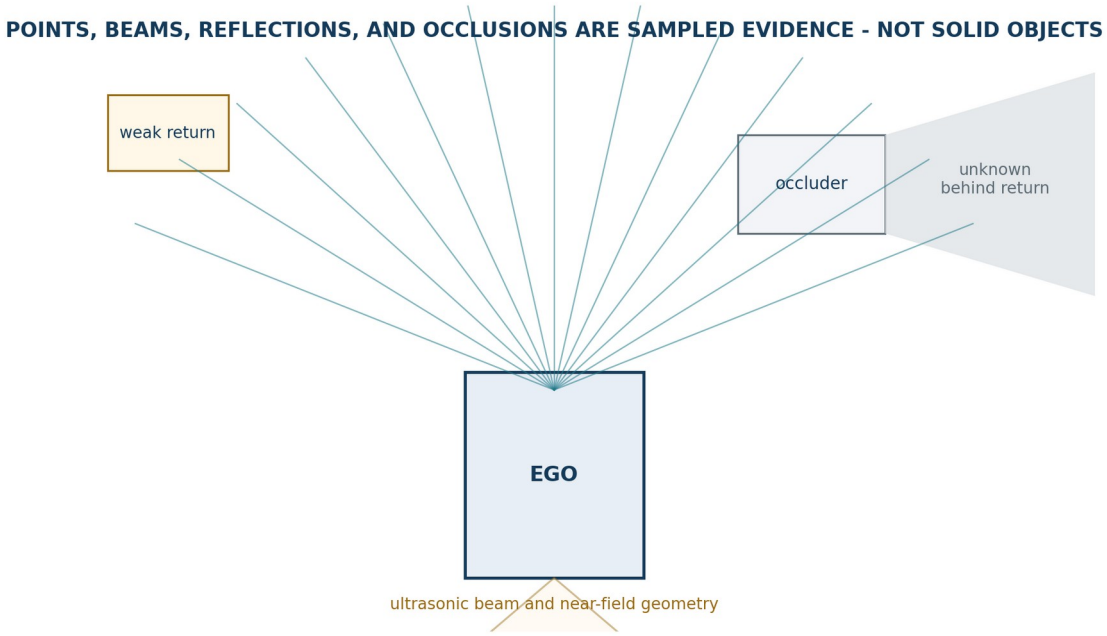


Figure 8.1. Original comparison of LiDAR point sampling, ultrasonic beam spread, occlusion, reflective loss, and short-range blind regions.

$$\text{ideal time-of-flight range } d = c \times \text{round\_trip\_time} / 2$$
$$\text{point\_vehicle} = T_{\text{vehicle\_sensor}} \times \text{point\_sensor}$$
$$\text{point\_spacing grows with range for a fixed angular sampling interval}$$

Point-cloud property	What it affects	Reasoning caution
Angular pattern	Coverage and point density	Mechanical, MEMS, flash, and solid-state designs sample differently
Range precision	Surface location along the beam	Precision is not the same as object-position accuracy
Intensity	Returned-energy indicator	Depends on calibration, range, material, angle, and device processing
Per-point time	Motion compensation and fusion	Treating a scan as one instant can distort moving scenes
No return	Missing surface evidence	May mean absorption, range limit, occlusion, weather, or geometry

Table 8.1. Point-cloud interpretation requires sampling and timing context.

LiDAR limitations and installation

Dark, highly absorptive, transparent, reflective, wet, or steeply angled surfaces can reduce or redirect returns. Rain, fog, snow, dust, and spray can attenuate light or create near-field returns. Direct sunlight and interference require design countermeasures. A roof-mounted sensor may see over nearby vehicles but adds cleaning and packaging challenges; a low bumper sensor has different occlusion and contamination behavior.

- Verify the sensor window, heater/cleaning function, mounting pose, and vibration state.
- Account for scan motion when the sensor or object moves during acquisition.
- Do not interpret an isolated point as a complete object without spatial and temporal support.
- Separate sensor range capability from detection range for a particular object and algorithm.
- Treat extrinsic calibration and time alignment as part of the 3D measurement chain.

Ultrasonic sensing at short range

Ultrasonic sensors transmit acoustic energy and estimate distance from echo timing. They are useful at low speed and short range for parking and nearby obstacle support. The speed of sound changes with air temperature and, to a lesser extent in ordinary automotive conditions, humidity and composition. Soft or angled surfaces may reflect little energy back; narrow poles, curbs, open meshes, and complex corners can be difficult. Cross-talk and multiple reflection paths can create false or delayed echoes.

$$\text{ultrasonic range } d = \text{speed\_of\_sound} \times \text{round\_trip\_time} / 2$$
$$\text{approximate speed of sound in air increases with temperature}$$

Concern	Evidence to inspect
No detection	Target material/angle/height, range zone, contamination, mounting, power, communication, diagnostic status
False obstacle	Water/ice, loose mounting, vibration, cross-talk, reflections from ground or body, software state
Wrong distance	Temperature compensation, sensor seating/orientation, paint/repair, multiple echoes, target geometry
Intermittent array	Shared harness/power, controller timing, connector sealing, recent bumper work, individual sensor response

Table 8.2. Short-range sensing must be evaluated with target geometry and installation state.

Choosing complementary evidence

Modality	Direct strengths	Typical gaps to cover
Camera	Appearance, color, texture, lane/sign semantics	Depth ambiguity, lighting and contrast dependence
Radar	Range, radial velocity, useful all-light operation	Angular/class detail, multipath and clutter
LiDAR	3D geometry and accurate sampled range	Weather/contamination, sparse distant sampling, cost/packaging
Ultrasonic	Near-field distance at low speed	Limited range/detail; acoustic reflection and cross-talk

Table 8.3. Sensor choice follows function, environment, architecture, and safety strategy.

Complementarity is not automatic redundancy. If two sensors share the same mounting obstruction, time source, power feed, training-data gap, or environmental vulnerability, their failures may be correlated. The architecture should identify independent and common causes, define which sensor is authoritative for which quantity, and specify how conflicts affect confidence and system behavior.

FUSION PREPARATION Before combining measurements, write down what each sensor directly measures, its frame and timestamp, expected uncertainty, failure modes, and validity indicators. Fusion cannot repair undefined inputs.

Point-cloud processing and adverse-weather reasoning

A point cloud is a set of sampled returns, not a solid surface. Processing may remove invalid points, compensate ego motion, transform frames, downsample into voxels, estimate the ground, cluster obstacles, and compute features. Each step can improve usability and also remove evidence. A ground filter tuned for a flat road may erase a low obstacle on a slope; coarse voxels can merge a pole and nearby background; motion compensation based on biased ego state can bend moving objects.

Rain, fog, snow, spray, dust, direct sunlight, contamination, and sensor-window heating or cleaning can affect range sensing differently. The correct response is not a universal claim that one sensor works or

fails in weather. Define the wavelength, sensor design, return-processing rules, severity, range, target, and cleaning state, then evaluate degradation and the system response when data quality falls below the function's need.

Processing step	Purpose	Possible hidden cost
Ego-motion compensation	Align points captured at different times	State or timestamp error warps geometry
Voxelization	Reduce data and form a regular structure	Thin or nearby objects merge or disappear
Ground removal	Separate road from above-ground obstacles	Curbs, slopes, debris, and low objects are misclassified
Clustering	Group returns into object hypotheses	Close actors merge; one actor fragments
Weather filtering	Suppress airborne or transient returns	Weak genuine obstacles are also removed

Table 8.3. Point-cloud processing trades noise reduction against evidence preservation.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. Why can a LiDAR scan of a moving vehicle appear geometrically distorted even if each range sample is accurate?
2. An ultrasonic sensor misses a low angled curb but detects a flat wall. Is that alone evidence of failure?
3. How can rain create both lost LiDAR range and extra near-field returns?
4. Why are camera and LiDAR not automatically independent just because their physics differ?

Answer notes

- Points are acquired at different times while the ego vehicle and target move. Without per-point timing and motion compensation, the assembled cloud treats a changing scene as one geometry.
- No. Target height, angle, material, beam pattern, specified detection zone, and documented feature behavior must be checked before classifying the observation.
- Water droplets and spray can scatter or attenuate outgoing and returning light, reducing energy from distant surfaces while producing closer atmospheric returns.
- They may share power, compute, calibration references, timestamps, mounting contamination, common training/scenario assumptions, or a fusion algorithm. Independence must be argued, not assumed.

CHAPTER TAKEAWAY LiDAR and ultrasonic sensors provide valuable range evidence under different conditions. Their point and echo outputs remain incomplete samples whose timing, geometry, environment, and installation must be understood.

CHAPTER 09 | EGO-STATE SENSING

IMU, GNSS, Wheel Speed, Steering, and Vehicle State

The vehicle must estimate its own motion before it can interpret surrounding motion or control a path with confidence.

Source anchors: R13, R19, R25

LEARNING OBJECTIVES

- Explain accelerometer, gyroscope, GNSS, wheel-speed, steering-angle, and yaw-rate contributions to ego state.
- Distinguish noise, bias, scale error, drift, latency, slip, and installation error.
- Describe dead reckoning and why absolute measurements are needed to constrain drift.
- Construct a vehicle-state confidence assessment across sensors and operating conditions.

Measuring the ego vehicle

A radar detection, camera lane, or LiDAR point is observed from a vehicle that is translating, rotating, vibrating, and changing speed. Ego-state estimation provides velocity, acceleration, orientation, yaw rate, position, and sometimes road-relative quantities needed to compensate that motion. Errors in ego state can make stationary objects appear to move, bend a reconstructed path, or shift localization even when the external sensor is healthy.

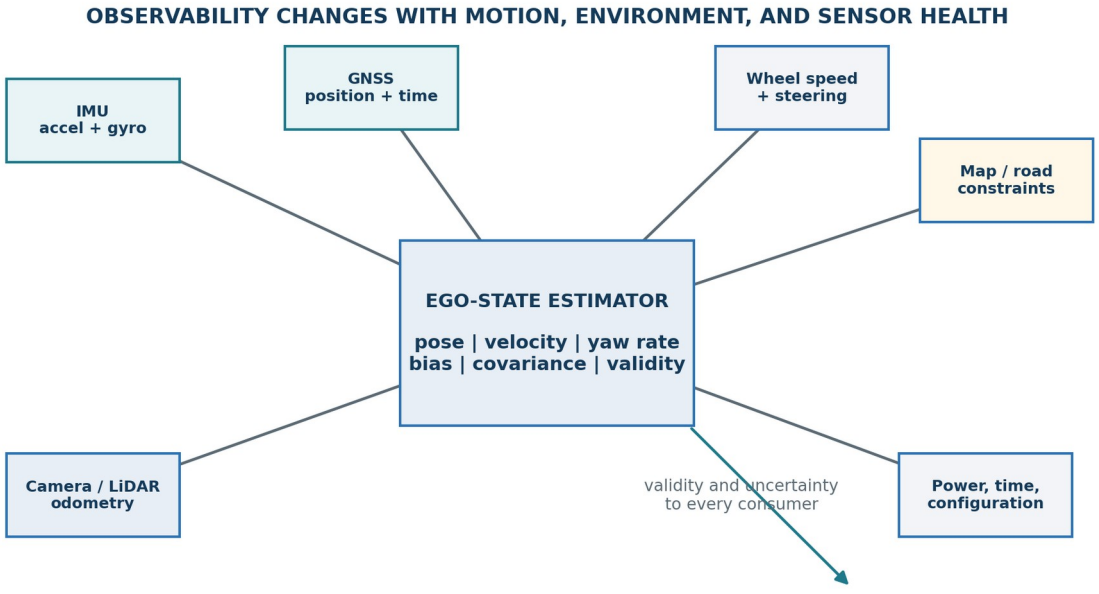


Figure 9.1. Original ego-state fusion map combining IMU, wheel speed, steering, GNSS, map constraints, and sensor odometry with bias and validity monitoring.

Source	Direct or derived contribution	Important limitations
Wheel speed	Individual wheel rotation; vehicle speed estimate	Tire radius, slip, wheel lift, mismatch, low-speed quantization
Steering angle	Driver/road-wheel command indicator	Ratio, compliance, offset, nonlinear geometry, actual tire force
Yaw-rate sensor	Rotation rate about vertical axis	Bias, installation orientation, vibration, temperature
Accelerometer	Specific force along sensor axes	Gravity projection, bias, scale, vibration, orientation
Gyroscope	Angular rate	Bias integration causes orientation drift
GNSS	Global position, time, and sometimes velocity	Blockage, multipath, atmosphere, integrity, update rate

Table 9.1. No single ego-state source is complete across all conditions.

IMU measurements and drift

An inertial measurement unit typically combines accelerometers and gyroscopes. An accelerometer measures specific force, not simply vehicle acceleration; gravity projected into the sensor axes must be considered. Gyroscope rate integrated over time estimates orientation change. Any bias accumulates: a small constant angular-rate error becomes growing heading error, and acceleration error integrated twice becomes rapidly growing position error.

$$\text{heading(t)} = \text{heading(0)} + \text{integral(yaw\_rate - estimated\_bias)}\ \text{dt}$$
$$\text{velocity(t)} = \text{velocity(0)} + \text{integral(acceleration)}\ \text{dt}$$
$$\text{position(t)} = \text{position(0)} + \text{integral(velocity)}\ \text{dt}$$

Bias can vary with temperature, aging, vibration, mounting stress, and sensor operating state. Scale-factor error changes measurement magnitude; misalignment rotates one physical motion into several axes; noise creates random variation. Calibration and filtering address different error classes. An apparently smooth signal may still contain bias, and filtering a biased signal does not create truth.

GNSS, maps, and dead reckoning

GNSS provides an absolute global reference and a precise time source under suitable reception. Urban canyons, tunnels, foliage, reflected signals, antenna problems, interference, and limited satellite geometry can degrade position. Receiver-reported accuracy or protection information must be interpreted as part of an integrity strategy, not treated as an unconditional promise.

Dead reckoning propagates pose from a previous state using motion measurements. Wheel speeds, steering, yaw rate, and IMU data can bridge short GNSS outages, but error grows without external correction. Map matching, visual landmarks, LiDAR localization, or high-quality GNSS updates can

constrain drift. The fusion logic must account for correlated errors and avoid snapping confidently to a wrong road or lane.

LOCALIZATION INTEGRITY Accuracy answers how close an estimate may be; integrity asks whether the system can trust that estimate enough for the intended decision and detect when it should not.

Vehicle-state plausibility

1. Define the state variables, frames, units, update rates, timestamps, and required accuracy.
2. Identify direct measurements and model-derived quantities; do not label both as equivalent sensor readings.
3. Compare independent physical relationships, such as yaw rate expected from speed, steering, and curvature.
4. Evaluate low-friction, tire-size, wheel-slip, reverse, standstill, grade, vibration, and temperature cases.
5. Inspect validity, covariance/confidence, reset behavior, and degradation when one source is lost.
6. Record mounting, alignment, tire, calibration, software, and time-source configuration with the dataset.

Plausibility is not a majority vote. Several signals can share one faulty source or common model. For example, vehicle speed distributed to multiple ECUs may originate from one estimate. A good evidence map distinguishes independent physics from repeated copies of the same information and recognizes when tire slip makes all wheel-derived speed estimates unreliable together.

Observability, bias, and graceful degradation

A state is observable when available measurements and motion make it possible to infer that state over time. A stationary vehicle cannot reveal every IMU bias from motion alone; straight constant-speed driving provides limited evidence about some lateral or heading errors. GNSS can bound long-term position drift but may be unavailable or multipath-corrupted. Wheel speed provides useful short-term motion but can be biased by tire size, slip, and wheel lift. Observability changes with maneuver and environment.

Bias estimation should be separated from immediate state estimation and guarded against false learning. If the system learns wheel-speed scale during tire slip or learns camera yaw during an incorrect map alignment, the correction can persist after the triggering condition disappears. Degraded operation should therefore report which states remain supported, how uncertainty grows, and which functions must reduce authority or become unavailable.

PLAUSIBILITY RULE Agreement among sensors is useful only when common causes are considered. Two values can agree because they share the same wrong time base, configuration, map, or vehicle-state input.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. Why does a stationary, slightly tilted accelerometer report acceleration components even when the vehicle does not move?
2. A vehicle drives through a tunnel. Which sources can bridge the GNSS loss, and what new uncertainty appears?
3. All four wheel speeds agree during wheel spin. Does agreement prove true vehicle speed?
4. How can a yaw-rate bias affect an apparently unrelated object-tracking result?

Answer notes

- Accelerometers measure specific force and gravity projects into sensor axes according to orientation. The measurement must be transformed and gravity-compensated for motion estimation.
- IMU, wheel speed, steering, yaw rate, and map constraints can propagate state, but bias, slip, scale, and model errors accumulate. Confidence should grow appropriately until an external reference returns.
- No. The wheels can share slip relative to the road, so agreement may reflect a common invalid assumption. Use additional motion evidence and operating context.
- Incorrect ego rotation compensation changes the transformed position and velocity of external detections, making stationary objects appear to move laterally or bending track histories.

CHAPTER TAKEAWAY Ego state is an estimate built from complementary, imperfect sources. Good localization and tracking depend on explicit frames, bias management, integrity monitoring, and honest growth of uncertainty during degraded conditions.

CHAPTER 10 | PERCEPTION AND ARTIFICIAL INTELLIGENCE

Machine Learning Foundations for ADAS

A learned model is not a box of intelligence; it is a versioned function shaped by data, labels, objectives, architecture, hardware, and the conditions under which it is evaluated.

Source anchors: R15, R26, R39, R40

LEARNING OBJECTIVES

- Explain training, validation, testing, inference, parameters, loss functions, and generalization without relying on programming jargon.
- Distinguish a learned model from the complete perception and vehicle function that surrounds it.
- Recognize dataset leakage, imbalance, annotation uncertainty, distribution shift, and shortcut learning.
- Interpret confidence scores, calibration, uncertainty, and threshold selection at a function level.
- Describe the evidence needed to trace an AI-enabled feature across data, model, software, hardware, and field monitoring.

What machine learning changes - and what it does not

Instead of writing every visual or geometric rule by hand, engineers define a model structure, an objective, and a training process that adjusts numerical parameters so the model produces useful outputs on representative data. During inference, the trained parameters are applied to a new camera image, radar tensor, point cloud, occupancy field, or fused feature set. The model can estimate classes, locations, masks, depth, lanes, motion, or trajectories, but it does not independently know whether a vehicle function should warn, brake, steer, or remain unavailable.

Term	Working meaning	Common misunderstanding
Training	Adjust model parameters using data and an objective	The model memorizes a complete set of driving rules
Inference	Apply frozen or deployed parameters to new input	Inference automatically includes validation and safety logic
Feature	A numeric representation useful to the model	Every feature is human-readable or physically meaningful
Label	A reference annotation created under a policy	A label is perfect ground truth without ambiguity
Loss	A training objective that penalizes selected errors	Lower training loss guarantees safer vehicle behavior
Generalization	Useful performance on relevant unseen conditions	A high aggregate test score covers every scenario

Table 10.1. Machine-learning terms describe parts of a lifecycle, not a complete safety claim.

A production feature usually surrounds the model with preprocessing, sensor validity checks, geometric transforms, temporal filtering, confidence logic, plausibility checks, fusion, state machines, driver communication, diagnostics, and fallback behavior. An excellent model can still be unsafe inside a poorly

timed or poorly integrated system. A modest model can be useful when its operating boundary is narrow, measured, and supported by conservative downstream logic.

Data partitions, labels, and leakage

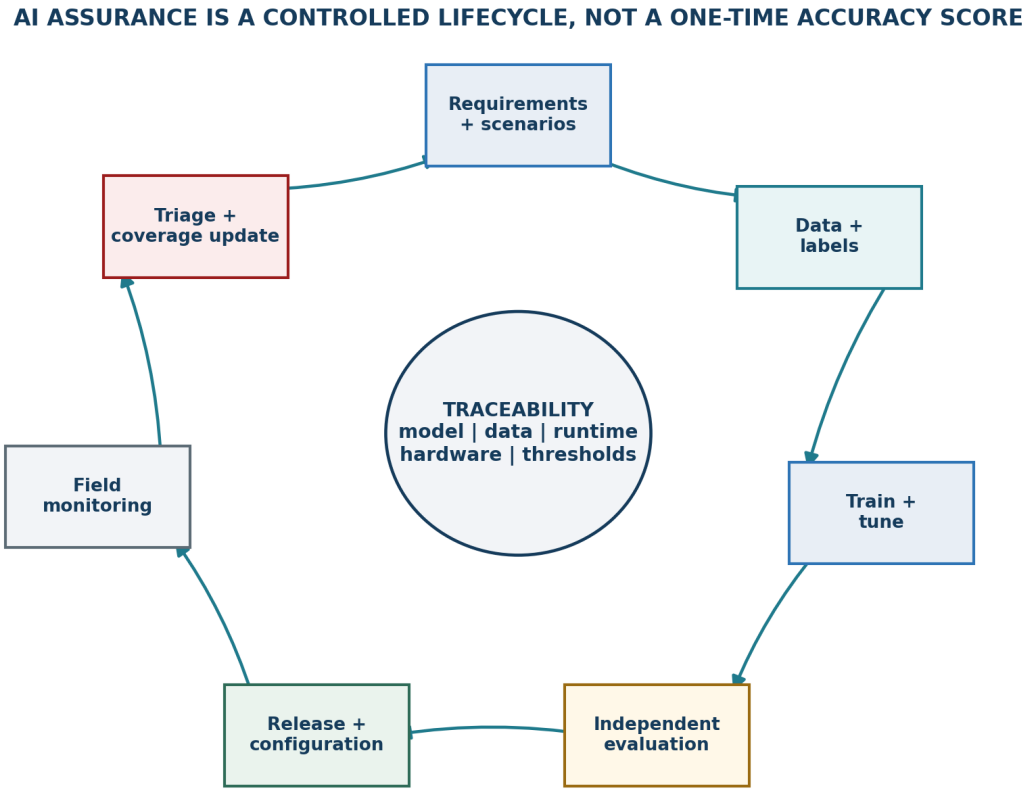


Figure 10.1. Original Project DRIVE model lifecycle: requirements and scenario coverage govern data, training, independent evaluation, deployment, and field evidence.

Training data teaches parameter values. Validation data supports design choices such as architecture, threshold, preprocessing, and hyperparameters. Test data is held back for a more independent estimate after those choices are fixed. The names alone do not guarantee independence. If nearly identical frames from the same drive, weather sequence, location, actor, or recording session appear in more than one partition, the reported result can look stronger than true generalization.

- Split by scene, route, time period, weather event, vehicle, sensor build, and recording campaign where those factors can create near-duplicates.
- Version the annotation policy as carefully as the images or point clouds; a changed definition can alter the apparent error rate.
- Preserve difficult, rare, and safety-relevant cases instead of allowing common easy scenes to dominate the score.

- Keep an untouched challenge set for important conditions that are likely to influence design decisions repeatedly.
- Record synthetic, augmented, and re-labeled data separately so their contribution and limitations remain visible.

LEAKAGE WARNING A model has effectively seen a test case when information from that case influenced training, threshold selection, preprocessing, label cleanup, architecture choice, or repeated design decisions. Leakage is broader than copying the same file into two folders.

Model families and learned representations

Convolutional networks use local filters and shared parameters to learn spatial patterns efficiently in images or grid-like inputs. Transformer-style models use attention mechanisms to relate information across positions or objects and can combine multiple views or time steps. Point-cloud models operate on irregular three-dimensional samples or convert them into pillars, voxels, or range images. Some systems transform camera, radar, and LiDAR features into a common bird's-eye-view representation before detecting objects or estimating occupancy.

Representation	Strength	Engineering question
Image feature map	Preserves appearance and fine image structure	How are depth, scale, occlusion, and camera geometry handled?
Point or voxel feature	Preserves sampled 3D geometry	What is lost through sparsity, filtering, voxel size, or range limits?
Object query or track feature	Compact actor-centered description	How are unknown space, missed actors, and identity changes represented?
Bird's-eye-view feature	Common road-plane geometry across sensors	How are height, overpasses, slopes, transform error, and occlusion preserved?
End-to-end latent state	Can optimize several stages jointly	Which intermediate failures, assumptions, and safety constraints remain observable?

Table 10.2. A representation makes selected information convenient and other information easier to lose.

The best architecture is task- and evidence-dependent. Larger networks can model more complex relationships but increase compute, memory, latency, thermal load, and validation scope. Compression, quantization, pruning, and hardware-specific acceleration can change numerical behavior. Therefore, model identity includes more than a file of weights: it includes preprocessing, postprocessing, runtime, accelerator, precision mode, calibration data, and thresholds.

Loss, metrics, confidence, and calibration

A loss function guides training by assigning numerical penalty to selected errors. Classification losses encourage correct categories; regression losses penalize errors in range, box geometry, keypoints, or motion; multi-task systems combine several terms with selected weights. Those weights encode

priorities but do not directly equal real-world harm. A model can reduce average loss by improving frequent easy cases while a critical minority case becomes worse.

$$\text{empirical\_loss} = \text{average of sample losses over the training data}$$
$$\text{total\_loss} = \text{w\_class L\_class} + \text{w\_geometry L\_geometry} + \text{w\_motion L\_motion} + \ldots$$
$$\text{calibration asks whether events predicted near probability p occur near frequency p}$$

A confidence score is a model output shaped by training and postprocessing. It is not automatically a calibrated probability and it is never a guarantee. Calibration evaluates whether score levels correspond to observed frequencies under a defined dataset. Even a well-calibrated model can be wrong on a new domain. Thresholds should be selected using function consequences, scenario partitions, and downstream mitigation rather than a single precision-recall curve.

CONFIDENCE BOUNDARY High confidence can occur for a confidently learned shortcut. Low confidence can occur for a genuine rare object. Review what evidence produced the score, where it was calibrated, and how the vehicle behaves when evidence conflicts.

Generalization, shift, robustness, and shortcuts

Distribution shift occurs when deployment input differs from development data. Weather, geography, traffic rules, construction, sensor aging, replacement glass, new optics, compression, firmware, mounting, road users, and rare events can all shift the data. Domain shift is not only visual. A new timestamp policy or vehicle-state source can change temporal and geometric relationships even when the image looks familiar.

Shortcut learning occurs when a model exploits a correlation that predicts labels in the development set but does not represent the intended concept. It might associate a background, recording artifact, annotation style, or sensor signature with a class. Counterfactual tests, controlled perturbations, cross-location evaluation, sensor-version partitions, saliency analysis used cautiously, and targeted error review can expose some shortcuts. None is a complete proof of causal understanding.

Robustness question	Useful evidence	Insufficient evidence alone
Does it tolerate ordinary variation?	Partitioned results across lighting, weather, range, occlusion, and actor types	One aggregate benchmark score
Does it detect unfamiliar input?	Out-of-distribution studies and defined degraded behavior	A maximum softmax or confidence score
Does it survive sensor change?	Hardware/version matrix and regression campaign	Same architecture name
Does it fail safely?	Function-level scenario tests, monitoring, fallback, and safety argument	Model accuracy in isolation

Table 10.3. Robustness requires partitioned, function-level evidence.

AI assurance and the deployed lifecycle

AI assurance connects the intended function to data coverage, model behavior, integration constraints, safety mechanisms, and field evidence. ISO/PAS 8800 provides an automotive AI-safety framework that can complement functional-safety and SOTIF work; NIST's AI Risk Management Framework offers a broader voluntary structure for governing, mapping, measuring, and managing AI risk. Neither source turns a metric into approval. Engineers still need a product-specific argument supported by traceable evidence.

1. Define the model's role, safety relevance, input contract, output contract, and prohibited assumptions.
2. Create a scenario and data-coverage argument tied to the ODD and foreseeable variation.
3. Trace dataset, label policy, preprocessing, model, runtime, hardware, threshold, and software configuration as one deployable item.
4. Evaluate both model-level metrics and vehicle-function consequences, including corrupted, missing, delayed, and conflicting input.
5. Specify monitors, degraded modes, logging, update criteria, rollback, and field-performance review before deployment.
6. Control every change and run targeted regression testing when any linked element changes.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. A test set contains frames immediately adjacent to training frames from the same drive. Why can the reported score be misleading?
2. A new model has better mean average precision but longer latency and worse nighttime pedestrian recall. What must be reviewed before release?
3. Why is a confidence score of 0.95 not automatically a 95 percent probability that the object is correct?
4. A model is unchanged, but the camera ISP firmware and neural-network accelerator runtime change. Is the deployed model effectively unchanged?
5. What evidence would help distinguish genuine visual understanding from a shortcut based on background or sensor artifacts?

Answer notes

- Adjacent frames share scene, actors, lighting, motion, and sensor artifacts. The model may be evaluated on near-duplicates rather than independent conditions, so generalization is overstated.
- Review function requirements, scenario severity and exposure, latency deadlines, nighttime partition performance, downstream mitigation, threshold behavior, compute/thermal effects, and regression evidence. No single aggregate metric decides release.

- The score may be uncalibrated, calibrated only on another distribution, or altered by postprocessing. Its meaning must be measured on relevant data and carried with domain limitations.
- No. Preprocessing and numerical execution are part of deployed behavior. Reproducibility, numerical tolerance, latency, thermal behavior, and function-level regression must be re-evaluated.
- Use controlled changes to backgrounds and artifacts, cross-location and cross-sensor evaluation, counterfactual scenes, targeted error review, and carefully interpreted feature-attribution evidence. Combine methods because each can mislead.

CHAPTER TAKEAWAY Treat a learned model as a traceable component in a larger safety-relevant system. Data independence, scenario coverage, calibration, integration, and field monitoring matter as much as architecture and aggregate accuracy.

CHAPTER 11 | PERCEPTION

Detection, Classification, Segmentation, Lanes, and Free Space

Perception converts sensor evidence into scene hypotheses; its outputs must carry geometry, confidence, timing, and class uncertainty into the rest of the vehicle.

Source anchors: R15, R16, R17, R26

LEARNING OBJECTIVES

- Distinguish detection, classification, semantic segmentation, instance segmentation, lane estimation, and free-space estimation.
- Explain precision, recall, intersection over union, confidence thresholds, and class confusion.
- Connect data quality, annotation, domain shift, and model behavior to validation evidence.
- Interpret perception output as a time-stamped hypothesis rather than an unquestioned fact.

Several different perception problems

Object detection proposes locations and categories for discrete actors. Classification assigns a category to an input or region. Semantic segmentation labels pixels or points by class without necessarily separating individual instances. Instance segmentation separates objects of the same class. Lane estimation describes boundaries or centerlines; free-space estimation describes traversable or unoccupied regions under defined assumptions. A production stack may combine these tasks because no single representation supports every driving decision.

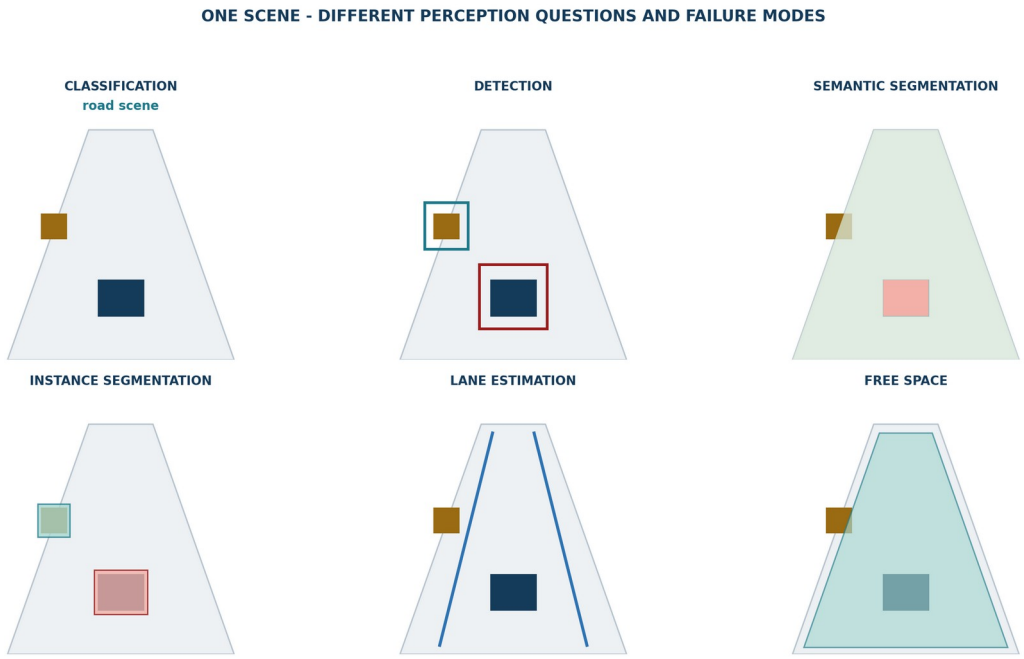


Figure 11.1. Original comparison of classification, detection, semantic segmentation, instance segmentation, lane estimation, and free-space output on one scene.

Output	Typical representation	Downstream use	Key uncertainty
Object detection	2D/3D box, class, score	Tracking, prediction, collision relevance	Extent, depth, class, occlusion
Semantic segmentation	Class label per pixel/point	Road, sidewalk, vegetation, markings	Boundary and rare-class confusion
Instance segmentation	Mask per object	Shape/overlap reasoning	Fragmentation or merged instances
Lane model	Polynomial, spline, points, confidence	Path and lane-support functions	Missing/ambiguous markings and topology
Free space	Grid, polygon, occupancy field	Local planning and obstacle avoidance	Unknown versus actually free

Table 11.1. Perception outputs answer different questions and expose different failure modes.

Metrics and threshold tradeoffs

A true positive is a correctly reported relevant instance under the evaluation definition. A false positive is a report without a matching relevant instance; a false negative is a missed instance. Precision measures how many reported positives are correct, while recall measures how many relevant instances were found. Changing a confidence threshold often trades one error type against the other. The correct operating point depends on function-level consequences, not on a universally best score.

$$\text{precision} = \text{TP} \;/\; (\text{TP} + \text{FP})$$
$$\text{recall} = \text{TP} \;/\; (\text{TP} + \text{FN})$$
$$\text{IoU} = \text{overlap\_area} \;/\; \text{union\_area}$$

Intersection over Union measures spatial overlap and is often used to decide whether a predicted box or mask matches a labeled reference. The threshold changes the metric. A box with acceptable overlap may still place the nearest edge poorly for collision reasoning, and a small localization error matters differently for a distant pedestrian than a large truck. Evaluation must include geometry and risk relevance, not only aggregate counts.

Data, labels, and domain shift

Perception models learn patterns from development data and labels created under a defined policy. Labels contain ambiguity: is a heavily occluded person still labeled; where does a reflective trailer end; how is an unusual mobility device classified; what counts as a lane boundary through a merge? Inconsistent policies can make model error and annotation disagreement look identical.

- Coverage: geography, season, lighting, weather, road design, actor types, and rare events.
- Balance: common scenes can dominate metrics while critical minority cases remain weak.
- Leakage: near-duplicate scenes across training and test sets inflate apparent generalization.
- Domain shift: new cameras, optics, compression, software, roads, or traffic behavior change the input distribution.
- Label quality: ambiguous or systematically biased ground truth limits the meaning of evaluation.
- Versioning: dataset, label policy, preprocessing, model, threshold, and hardware must be traceable together.

UNKNOWN IS A VALID STATE A system should not silently convert insufficient evidence into 'free,' 'no object,' or a confident familiar class. Unknown or low-confidence output can be the safest and most truthful representation.

From frame result to temporal scene

A frame-level detection becomes more useful when connected over time. Temporal consistency can reject isolated noise, recover through brief occlusion, estimate velocity, and improve class stability. It can also preserve a mistake: an incorrect association may carry a wrong class or trajectory forward. Perception and tracking must exchange measurement uncertainty, timestamps, shape, and validity rather than only a hard label.

1. Define the scene element and the decision it supports.
2. Specify output geometry, frame, timestamp, class set, confidence meaning, and unknown handling.
3. Choose metrics that expose both average performance and safety-relevant error categories.
4. Partition evaluation by distance, occlusion, lighting, weather, actor type, roadway, and sensor version.

5. Review false positives and false negatives as scenarios, not only counts.
6. Trace perception errors into tracking, planning, control, driver interaction, and fallback behavior.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. A model's overall recall improves, but pedestrian recall at night decreases. Is the new model better?
2. Why can an occupancy grid cell marked 'not occupied' be unsafe to interpret as 'known free'?
3. A detector reports the correct class but the box is shifted. Which downstream functions may still be affected?
4. How can a higher confidence threshold reduce false positives while increasing system risk?

Answer notes

- The aggregate metric cannot answer. The decision depends on requirements, scenario exposure, severity, uncertainty, and other regressions. The nighttime decrease may be unacceptable even with a higher average.
- The cell may be unobserved, occluded, outside range, or below detection confidence. Free space requires affirmative evidence and an explicit unknown state.
- Association, range/position fusion, collision-path overlap, lane relation, prediction, and planning can be wrong even when class is correct.
- It may suppress weak but genuine critical detections, increasing false negatives. Threshold choice must be evaluated at function level with relevant scenarios and mitigation logic.

CHAPTER TAKEAWAY Perception outputs are structured hypotheses with geometry, class, time, and uncertainty. Metrics become meaningful only when tied to scenario categories and downstream consequences.

PART 3

Localization, Scene Representation, Tracking, and Fusion

Chapters 12-17

Transform asynchronous evidence into spatially and temporally consistent ego, object, occupancy, and risk estimates.

CHAPTER 12 | LOCALIZATION AND ALIGNMENT

Localization, Maps, Calibration, and Time Synchronization

Spatial alignment and temporal alignment are one problem: determine where each measurement belongs when it was actually observed.

Source anchors: R13, R15, R19, R25

LEARNING OBJECTIVES

- Distinguish global, map-relative, lane-relative, and ego-relative localization.
- Explain intrinsic, extrinsic, temporal, and vehicle-reference calibration roles.
- Estimate how latency and clock error become spatial error in moving scenes.
- Describe map layers, map uncertainty, and localization integrity without treating maps as ground truth by default.

Localization is a relationship, not a dot

Localization estimates the vehicle's position and orientation relative to a coordinate system or map. A global GNSS pose, a position within a high-definition map, and a lateral offset from a visible lane boundary answer different questions. Their uncertainty can be different in longitudinal, lateral, and heading directions. The estimate should therefore include a frame, timestamp, covariance or integrity indication, source configuration, and map version where applicable.

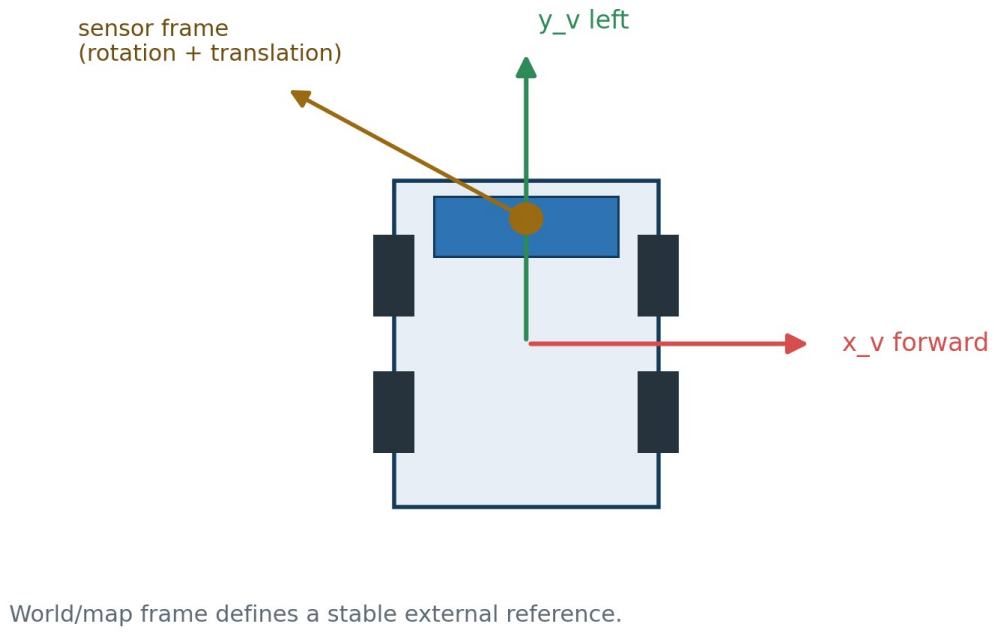


Figure 12.1. Sensor, vehicle, and world relationships must be spatially and temporally consistent before localization evidence can be fused.

Localization form	Reference	Useful for	Primary vulnerability
Global	Earth-fixed/geodetic	Geofence, route, fleet position	GNSS blockage, multipath, projection and datum errors
Map-relative	Feature or HD map	Lane-level planning and ODD checks	Map freshness, association to wrong feature, localization-map coupling
Lane-relative	Observed or mapped lane	Lane support and path centering	Missing/ambiguous markings, merges, construction
Ego-relative	Vehicle body frame	Local objects, free space, immediate control	Ego pose and sensor extrinsic error

Table 12.1. A localization claim must state the reference and intended use.

Maps are versioned sensor-like evidence

A navigation map may represent road connectivity and routing. A higher-definition map can add lane geometry, boundaries, signs, stop lines, elevation, or localization features. No map is the live world. Construction, shifted lanes, temporary closures, snow cover, and changed signs can invalidate assumptions. Map provenance, creation date, update process, coordinate frame, resolution, and confidence matter just as sensor calibration and timestamp matter.

- Geometry layer: centerlines, boundaries, curvature, elevation, and lane connectivity.
- Semantic layer: lane type, traffic controls, speed information, right-of-way, and restrictions.

- Localization layer: stable features used to align live sensor observations with the map.
- Dynamic layer: temporary traffic, construction, closures, or condition updates where supported.
- Integrity layer: map version, freshness, coverage, uncertainty, and detected conflict with live observations.

MAP CONFLICT When live perception and a map disagree, do not choose the source with the more polished display. Evaluate freshness, visibility, localization confidence, feature geometry, and the consequence of each possible error.

Calibration as a transform estimate

Calibration estimates parameters needed to interpret measurements. Camera intrinsic calibration links pixels to optical rays. Sensor extrinsic calibration estimates rotation and translation between frames. Vehicle service calibration can establish or restore the installed relation among sensor, target/reference, and vehicle geometry according to an OEM process. Time calibration estimates clock offset, drift, latency, or exposure/measurement timing. These are related but not interchangeable operations.

Calibration type	Parameter relationship	Example failure signature
Intrinsic	Internal sensor model	Curved lines or rays map incorrectly across the image
Extrinsic	Sensor pose relative to vehicle/other sensor	Consistent lateral, vertical, or angular mismatch across sensors
Temporal	Clock offset, drift, latency, scan/exposure timing	Mismatch grows with speed or changes direction with motion
Vehicle reference	Installed system to OEM-defined geometry	Function bias after body, glass, suspension, alignment, or mounting work

Table 12.2. Different calibration parameters produce different evidence patterns.

Calibration quality must be judged against the function. A mean reprojection error can hide a localized edge error; a good static target fit may not reveal timing offset; a dynamic self-calibration can converge to a wrong local solution if motion or features are insufficient. Independent validation points and operating scenarios help determine whether the estimated transform generalizes.

Time turns into distance

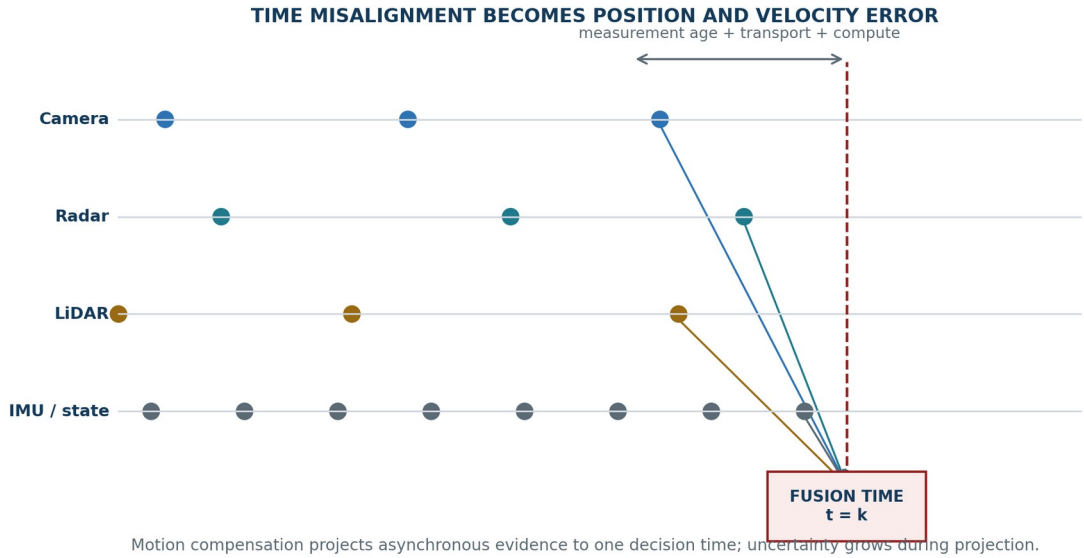


Figure 12.2. Original timing diagram aligning camera, radar, LiDAR, IMU, and vehicle-state measurements to a common fusion time using timestamps and motion compensation.

Sensors run at different rates and may timestamp data using different clocks. Images have exposure intervals; radars have chirp and processing cycles; LiDAR scans can span a meaningful fraction of a second; network and compute queues add latency. Fusion needs the measurement time, not simply the time a message arrived. Clock synchronization limits, delay compensation, buffering policy, and out-of-sequence handling belong in the interface definition.

$$\text{longitudinal spatial error approximately speed x time\_offset}$$
$$\text{at } 30 \text{ m/s}, 50 \text{ ms corresponds to about } 1.5 \text{ m of ego travel}$$
$$\text{angular mismatch approximately relative\_yaw\_rate x time\_offset}$$

1. Identify the clock domain and timestamp creation point for every measurement.
2. Measure or bound transport, buffering, processing, and actuation latency rather than assuming nominal rates.
3. Transform measurements to a common spatial frame at a common comparison time using ego motion where appropriate.
4. Propagate uncertainty added by interpolation, extrapolation, scan motion, and clock error.
5. Create tests with stationary, longitudinal, lateral, and turning motion to separate spatial from temporal bias.
6. Verify synchronization and transforms after software, sensor, gateway, or configuration changes.

SLAM, smoothing, and factor-graph intuition

Simultaneous localization and mapping estimates vehicle motion while building or refining a representation of the environment. It is valuable when an accurate prior map is unavailable, but loop closure, repeated structure, moving objects, and long-term map change create difficult data-association problems. A locally consistent trajectory can still be globally shifted or rotated.

Filtering updates the current state recursively, while smoothing uses later measurements to improve estimates of earlier states. Factor graphs express states and measurement constraints as a network and solve for a trajectory or map that best satisfies them under uncertainty. These methods are powerful offline and online tools, but the same fundamentals remain: correct frames, timestamps, noise models, association, robust handling of outliers, and honest uncertainty.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. Camera and radar detections align when stationary but separate during fast lateral motion. Which hypothesis deserves priority?
2. Why should an HD map not automatically overrule a clearly observed temporary lane shift?
3. At 20 m/s, what longitudinal offset can a 100 ms timestamp error create before other errors are considered?
4. How would you distinguish a constant extrinsic yaw error from a timing error using scenarios?

Answer notes

- Temporal alignment, processing latency, scan/exposure timing, and motion compensation are strong candidates because the mismatch is motion dependent; spatial calibration still needs independent confirmation.
- Maps can be stale or have localization error. Live evidence, map freshness, confidence, construction context, and a safe conflict strategy must be evaluated.
- The simple speed-times-delay estimate is 2 m. The real error may also include acceleration, object motion, transform, and buffering effects.
- A spatial yaw bias tends to produce a repeatable angle-dependent displacement even in static scenes. A timing error is small while stationary and changes with relative motion, speed, or yaw rate.

CHAPTER TAKEAWAY Localization, mapping, calibration, and synchronization form one geometry-and-time discipline. Measurements should meet only after their frames, timestamps, versions, and uncertainties are made compatible.

CHAPTER 13 | SCENE REPRESENTATION

Occupancy Grids, Bird's-Eye View, and Scene Representation

The system can reason only with what its scene representation preserves; occupied, free, and unknown space must remain meaningfully different.

Source anchors: R15, R19, R29

LEARNING OBJECTIVES

- Compare object lists, occupancy grids, bird's-eye-view features, vector maps, and scene graphs.
- Explain occupied, free, and unknown evidence and why absence of a detection is not proof of free space.
- Describe inverse sensor models, probabilistic updates, ego-centric and map-centric frames, and resolution tradeoffs.
- Connect static occupancy, dynamic occupancy, flow, occlusion, and reachable space to planning decisions.
- Define validation evidence for spatial representations beyond a single global overlap score.

A representation is an engineering decision

An object list is compact and convenient for actor tracking, but it can omit irregular obstacles and unknown space. A grid describes space directly but consumes memory and depends on cell resolution. A vector map preserves lanes, boundaries, and topology but may be stale or unavailable. A scene graph expresses relationships such as vehicle-in-lane or pedestrian-near-crosswalk but depends on upstream estimates. Many systems use several representations and transform information among them.

Representation	Preserves well	Can hide or simplify
Object list	Identity, class, pose, velocity, covariance	Unmodeled shape, free/unknown space, diffuse obstacles
Occupancy grid	Spatial evidence with occupied/free/unknown states	Object identity, fine shape below cell size, height in a 2D grid
BEV feature map	Common road-plane alignment across sensors and views	Projection uncertainty, vertical structure, physical interpretability
Vector map	Lane geometry, rules, topology, semantic landmarks	Temporary changes, unmapped areas, map freshness
Scene graph	Actors and meaningful relationships	Continuous geometry and low-level uncertainty

Table 13.1. Scene representations answer different downstream questions.

Occupancy, free space, and unknown space

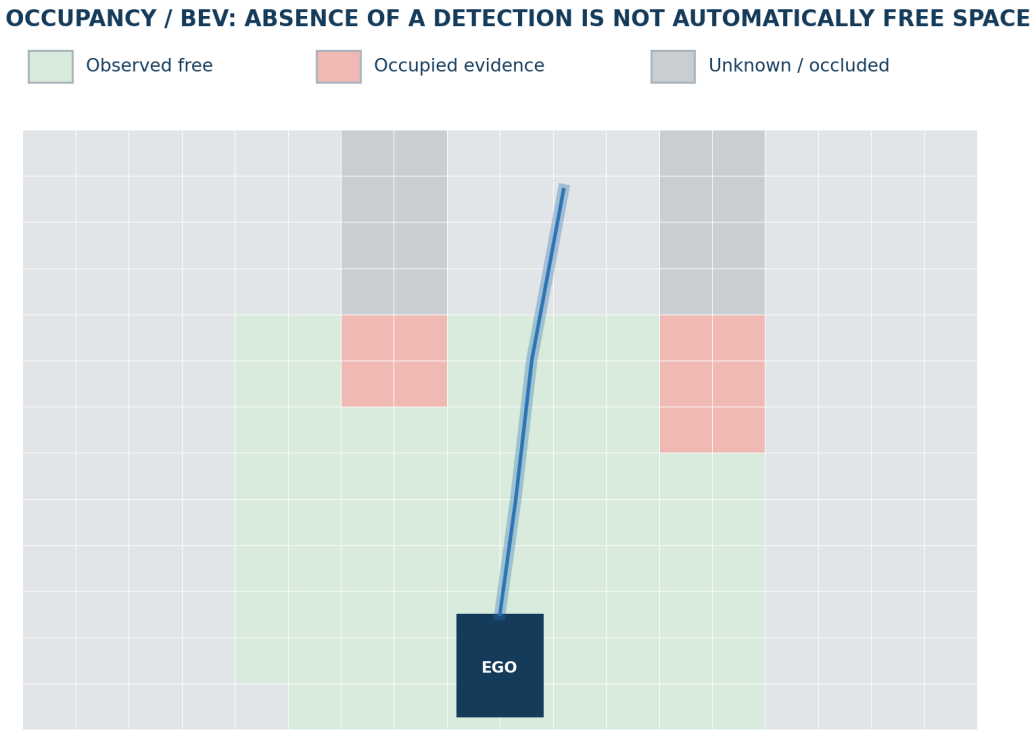


Figure 13.1. Original occupancy and bird's-eye-view diagram separating observed free cells, occupied evidence, occluded unknown space, and a planned corridor.

An occupancy grid divides space into cells and estimates whether each cell is occupied. A sensor ray can provide evidence that cells before a measured return are free and that a cell near the return is occupied. Cells behind the return may remain unknown because the sensor cannot see through the obstacle. A missed detection, out-of-range region, reflective failure, or unobserved area must not be silently converted to free.

$$\text{odds(occupied | evidence)} = \text{probability} \ / \ (1 \text{ - probability})$$

$$\text{log\_odds\_new} = \text{log\_odds\_prior} + \text{log\_odds\_sensor} \text{ - } \text{log\_odds\_reference}$$

$$\text{cell\_size trades geometric detail against memory, compute, noise sensitivity, and update rate}$$

An inverse sensor model describes how a measurement changes occupancy belief along the measurement geometry. The model must reflect sensor resolution, beam width, range noise, multipath, dropout, and installation uncertainty. Treating every LiDAR point, radar return, or ultrasonic echo as a perfectly located occupied cell creates false precision. Conversely, aggressive filtering can erase weak but relevant evidence.

THREE-STATE DISCIPLINE Known free, likely occupied, and unknown are different evidence states. Planning through unknown space requires a deliberate risk policy; it is never justified merely because no object was reported.

Bird's-eye view and coordinate consistency

Bird's-eye view places information in a top-down coordinate system, often centered on the ego vehicle or a map frame. Camera features may be lifted through estimated depth and projected onto the road plane; radar and LiDAR information can be transformed from their sensor frames. A common grid simplifies cross-sensor fusion and local planning because lanes, actors, and candidate paths share geometry.

The transformation does not remove uncertainty. Camera depth error stretches along viewing rays. Radar angular uncertainty spreads returns laterally. LiDAR becomes sparse with range. Pitch, roll, road grade, timestamp mismatch, and calibration bias can shift features into the wrong cells. A flat-ground assumption may fail on crests, dips, ramps, loading docks, and multi-level roads. A responsible BEV design carries transform validity and vertical context rather than presenting a crisp top-down image as ground truth.

Frame choice	Advantage	Required caution
Ego-centric	Simple local geometry and bounded memory	The world shifts as the vehicle moves; history must be motion-compensated
Map-centric	Stable global accumulation and route context	Localization and map error directly distort the representation
Sensor-centric	Preserves raw measurement geometry	Downstream modules must handle multiple frames and coverage patterns
Road-aligned	Convenient lane-relative reasoning	Road model and topology can be ambiguous or temporarily wrong

Table 13.2. Frame selection changes both convenience and failure propagation.

Dynamic occupancy, flow, and reachable space

Static occupancy answers where evidence suggests matter is present now. Dynamic occupancy adds motion estimates or future occupancy probability. An occupancy-flow field can represent how occupied mass is expected to move across cells. This is useful for actors that are difficult to maintain as clean object tracks, but it can blur identities and multimodal futures. A pedestrian near a curb may plausibly continue, stop, or enter the lane; collapsing those futures into one average velocity can create a path that no actor will actually take.

Reachability asks which future states are physically possible for the ego vehicle or another actor under bounded motion. A planned corridor should be checked against predicted occupancy, uncertainty growth, road and vehicle constraints, and stopping capability. Occlusion matters because another actor

may emerge from unknown space. Conservative planning can enlarge risk buffers near occluded crosswalks, parked vehicles, and blind intersections without pretending the hidden actor is known.

1. Define the grid frame, cell size, spatial extent, vertical treatment, update rate, and time horizon.
2. Specify how each sensor contributes free, occupied, and unknown evidence, including occlusion and invalid input.
3. Compensate for ego motion and measurement time before accumulating evidence.
4. Represent dynamic state, uncertainty, and multiple plausible futures where the decision requires them.
5. Trace the representation into collision checking, speed choice, path planning, and fallback behavior.

Resolution, validation, and failure analysis

Smaller cells preserve more geometric detail but increase memory, bandwidth, and compute and can make noise look structurally important. Larger cells are efficient but can merge a curb, narrow post, motorcycle, and adjacent free space. A multi-resolution design may use fine cells near the vehicle and coarser cells farther away. The choice must match stopping distance, vehicle footprint, required clearance, sensor resolution, and planning horizon.

Validation slice	Question
Range and angle	Does occupancy quality change across the sensor field and near coverage boundaries?
Object geometry	Are thin, low, overhanging, partially visible, or irregular obstacles represented appropriately?
Occlusion	Does the system preserve unknown space and react conservatively to emerging actors?
Motion	Are fast, crossing, stopped, reversing, and multimodal actors represented without harmful averaging?
Timing and transforms	What happens under latency, ego-motion error, calibration bias, or map/localization error?
Function consequence	Do representation errors change collision checks, planned clearance, speed, or fallback?

Table 13.3. Spatial validation should expose where representation error matters to action.

Cell accuracy or intersection-over-union can be useful, but global scores hide rare occupied cells and unknown-space mistakes. Evaluate occupied and free evidence separately, preserve an unknown category, partition by distance and object type, and replay errors through planning. A small false-free region on the intended path can matter more than thousands of correctly labeled distant cells.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. A grid cell has no LiDAR points. Under what conditions can it be called free rather than unknown?
2. Why can a finer grid reduce system performance even though it preserves more detail?
3. Camera and radar features align in BEV at standstill but separate during turns. Which evidence should be investigated?

4. A dynamic occupancy model predicts one average path for a pedestrian with two plausible futures. What is the risk?
5. Why can a high global occupancy score still hide a dangerous defect?

Answer notes

- Only when the sensor model and valid measurement geometry provide affirmative free-space evidence through that cell. Out-of-range, occluded, filtered, invalid, or simply unobserved cells remain unknown.
- It increases memory, bandwidth, compute, and noise sensitivity and can reduce update rate. Slower or delayed spatial evidence may be worse than a well-chosen coarser representation.
- Check timestamps, ego-motion compensation, yaw rate and steering state, sensor extrinsics, frame conventions, latency, interpolation, and the turn-dependent assumptions in the projection.
- The average can fall between real futures and understate risk in both. Preserve multiple modes or a probability field that covers plausible occupancy.
- Most cells are easy background. A small false-free region, thin missed obstacle, or occlusion error on the planned corridor can be safety-relevant while barely changing the average.

CHAPTER TAKEAWAY Scene representation is part of the safety argument. Preserve occupied, free, and unknown evidence, carry timing and transform uncertainty, and validate errors where they affect the vehicle's reachable path.

CHAPTER 14 | OBJECT TRACKING

Data Association and Gating

The first tracking question is not where an object will go; it is whether this measurement belongs to that object at all.

Source anchors: R14, R15, R19

LEARNING OBJECTIVES

- Explain nearest-neighbor, probabilistic, and assignment-based association ideas at a systems level.
- Construct validation gates using predicted measurements and uncertainty.
- Recognize ambiguous crossings, occlusion, clutter, duplicate detections, and sensor-specific association errors.
- Describe why association mistakes can be more damaging than a noisy measurement.

From detections to identities

A tracker predicts where each existing object should appear, then compares new measurements with those predictions. If a measurement is compatible, it may update that track. Otherwise, it may begin a new track, remain unassigned clutter, or contribute to a more complex multi-hypothesis decision. Association uses position, velocity, shape, class, sensor origin, and time, but every added feature carries its own uncertainty and failure modes.

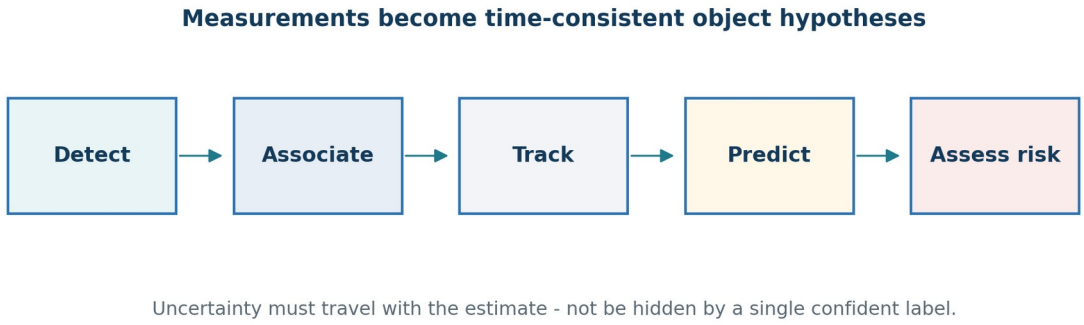


Figure 14.1. Original tracking workflow from detections through prediction, gating, association, update, and lifecycle management.

Association cue	Benefit	Risk
Position/distance	Simple spatial compatibility	Dense scenes and unequal uncertainty create wrong nearest matches
Velocity	Separates crossing or adjacent actors	Noisy or radial-only measurements can mislead
Class	Prevents implausible category switches	Classifier errors can block the correct match
Shape/extent	Supports object continuity	Occlusion and view angle change visible shape
Appearance	Useful for image-based re-identification	Lighting, viewpoint, privacy, and domain shift
Track history	Rewards temporal consistency	A past mistake can become self-reinforcing

Table 14.1. Association features help only when their reliability is represented honestly.

Gating with uncertainty

A validation gate removes measurements that are too inconsistent with a track prediction to be plausible. A fixed circular distance gate is easy to understand but ignores different uncertainty along different axes. A covariance-aware gate uses the innovation: the difference between the actual measurement and the measurement predicted from the track. The innovation covariance describes expected variation from both track and measurement uncertainty.

$$\text{innovation } y = z - H\ x_{predicted}$$
$$\text{innovation\_covariance } S = H\ P_{predicted}\ H^{\wedge}T + R$$
$$\text{normalized\_distance\_squared} = y^{\wedge}T\ S^{\wedge}\text{-}1\ y$$

The normalized distance creates an elliptical gate aligned with uncertainty. A larger covariance produces a larger gate, preserving possible matches after occlusion but admitting more clutter. A smaller covariance is selective but can reject the true measurement if confidence is overstated. Gate tuning is therefore connected to process noise, sensor covariance, missed-detection strategy, and scene density.

Assignment and ambiguity

When several tracks and measurements share gates, association becomes a global assignment problem. Greedy nearest-neighbor matching can consume a measurement that would have been the only plausible choice for another track. A cost matrix can represent normalized distance and other cues, and an assignment algorithm can seek a low-cost one-to-one solution. More advanced methods maintain association probabilities or several hypotheses over time when the evidence does not justify an immediate hard choice.

Approach	Strength	Boundary
Nearest neighbor	Fast, transparent, effective in sparse scenes	Brittle in crossings, clutter, and unequal uncertainty
Global assignment	Considers competing matches together	Still requires good costs, gates, and missed-detection handling

Approach	Strength	Boundary
Probabilistic association	Represents ambiguity instead of one hard match	Can blend nearby objects and increase computation
Multiple hypotheses	Delays irreversible choice across time	Hypothesis growth requires pruning and careful scoring

Table 14.2. Association method should match scene density, compute, and safety consequences.

IDENTITY RISK A low-residual measurement can still belong to the wrong actor. Geometry must be combined with temporal, kinematic, and scene evidence, especially during merges and crossings.

Association validation scenarios

1. Begin with separated constant-velocity actors to establish the baseline.
2. Add measurement noise and unequal covariance; verify that gates change as intended.
3. Create side-by-side, merge, cut-in, crossing, and overtaking trajectories.
4. Insert missed detections, duplicate detections, false alarms, class changes, and delayed measurements.
5. Measure identity switches, fragmentation, false tracks, track loss, and recovery time in addition to position error.
6. Inspect each severe failure as a time sequence and trace its possible function-level consequence.

Average tracking error can remain low while identity switches occur at the most critical moment. Project DRIVE exercises therefore visualize track IDs and association lines frame by frame. The aim is to make the discrete decision visible, explain why the cost favored it, and decide whether the system should maintain ambiguity, degrade confidence, or change behavior.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. Why can increasing a gate reduce track loss but increase identity switches?
2. Two pedestrians cross and one detection is missed. Which evidence can help preserve identity?
3. A tracker has low position RMSE but frequent ID switches. Is it suitable for behavior prediction?
4. Why can using class as a hard association rule be dangerous?

Answer notes

- A larger gate keeps the true but uncertain measurement eligible, while also admitting more measurements from neighboring actors and clutter. Assignment ambiguity grows.
- Predicted motion and covariance, appearance if appropriate, shape, prior velocity, occlusion geometry, class uncertainty, and multiple-hypothesis history can help. None guarantees identity alone.
- Not necessarily. Prediction and risk assessment depend on continuous actor history; identity switches can attach the wrong behavior or trajectory even when instantaneous positions are accurate.
- Class estimates can fluctuate under occlusion or unusual views. A wrong class may reject the correct measurement and force an identity switch. Use class probabilistically with other cues.

CHAPTER TAKEAWAY Association is a discrete uncertainty problem at the center of tracking. Gates and costs should expose ambiguity rather than manufacture confidence from the nearest plausible point.

CHAPTER 15 | OBJECT TRACKING

Track Management and Motion Models

A track is a maintained hypothesis with a lifecycle, not merely the latest detection stored under an ID.

Source anchors: R14, R15, R19

LEARNING OBJECTIVES

- Define tentative, confirmed, coasting, and deleted track states.
- Compare constant-position, constant-velocity, constant-acceleration, and turn-aware motion models.
- Explain how missed detections, false alarms, occlusion, and process noise affect lifecycle policy.
- Evaluate tracking with identity, continuity, latency, and safety-relevant metrics.

The track lifecycle

A new detection may be clutter, a duplicate, or a real actor. Track initiation often requires repeated compatible evidence before confirmation. A confirmed track can survive a limited number of missed detections by propagating its state, a condition often called coasting. If evidence remains absent or implausible, the track is deleted. The timing of these transitions trades false tracks against detection delay and premature loss.

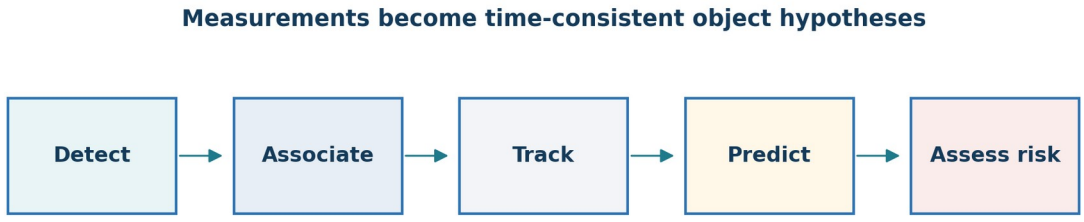


Figure 15.1. Tracking combines continuous state estimation with discrete lifecycle decisions.

Lifecycle state	Purpose	Key policy questions
Tentative	Test whether new evidence is persistent	How many hits, over what time, with what spatial consistency?

Lifecycle state	Purpose	Key policy questions
Confirmed	Expose a stable actor estimate downstream	What existence confidence and quality are required by each consumer?
Coasting	Bridge brief occlusion or missed detection	How fast should covariance grow and which outputs remain usable?
Deleted	Remove unsupported hypothesis	Can the ID be reused; how are late measurements and reappearance handled?

Table 15.1. Lifecycle policy is part of function latency and false-alarm behavior.

Motion-model choices

A motion model predicts how state evolves between measurements. A constant-position model is useful for nearly stationary objects or very short intervals. Constant velocity assumes velocity persists; constant acceleration extends the state to represent changing speed. Turn-aware models represent heading and yaw behavior. More complexity can reduce systematic residuals in the right maneuvers but introduces more states, tuning, initialization needs, and ways to become unstable.

Model	Useful regime	Expected failure
Constant position	Stationary or low-motion objects	Lags moving actors and inflates residuals
Constant velocity	Short-horizon, smooth motion	Lags acceleration and turning
Constant acceleration	Sustained acceleration/deceleration	Can overreact to noisy acceleration and unmodeled turns
Coordinated turn	Approximately constant turn rate and speed	Fails during abrupt lane changes or changing turn rate
Multiple-model	Mixed maneuvers and transitions	Mode probabilities and compute require careful validation

Table 15.2. Model choice should follow residual evidence and decision horizon.

Process noise represents uncertainty in the motion model, including maneuvers not explicitly modeled. Too little process noise creates an overconfident track that rejects real maneuvers; too much produces a wandering estimate and broad association gates. Tuning should be evaluated by scenario category and residual consistency, not solely by minimizing a single position-error metric.

Occlusion, duplicates, and track quality

Occlusion is structured missing information. A pedestrian passing behind a parked vehicle has a plausible hidden region and reappearance boundary. A tracker can propagate the hypothesis while increasing uncertainty, but should not pretend to observe the hidden actor. Duplicate tracks can occur when one physical object produces separated clusters or when a reappearing object starts a new track before the old one is reconciled.

- Existence confidence: evidence that the physical actor is real and still present.
- State quality: uncertainty in position, velocity, acceleration, heading, and extent.

- Classification quality: confidence and stability of semantic labels.
- Freshness: time since direct supporting measurement and number of consecutive misses.
- Consistency: residual history, sensor agreement, and plausibility with road geometry.
- Use restriction: whether the track is suitable for display, prediction, planning, or emergency action.

COASTING HONESTY A coasted track is a prediction supported by history, not a current observation. Downstream consumers need freshness and uncertainty so they can use it appropriately.

Tracking evidence beyond RMSE

Root-mean-square position error summarizes continuous accuracy but can hide identity switches, fragmented trajectories, false tracks, long confirmation delays, or unsafe loss near collision. Evaluation should include detection-to-confirmation latency, deletion timing, time tracked, identity continuity, false-positive track duration, occlusion recovery, velocity/heading error, uncertainty calibration, and the effect on the receiving function.

1. Define the downstream decision and the state quality it requires.
2. Create scenario families for steady motion, acceleration, braking, turns, cut-ins, crossings, occlusion, and clutter.
3. Measure confirmation and deletion delay as well as state error.
4. Review track IDs and existence confidence over time against labeled actor histories.
5. Check whether stated covariance contains actual errors at the expected frequency and by scenario.
6. Trace the worst failures into prediction, warning, planning, or control impact.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. What happens if a tracker confirms new tracks too quickly in a cluttered scene?
2. Why should uncertainty grow while a track coasts through occlusion?
3. A constant-velocity track consistently trails a braking target. Which model assumption is exposed?
4. Why can reusing a deleted track ID create analysis errors?

Answer notes

- False detections can become exposed tracks with little evidence, increasing false warnings, planning noise, and duplicate identities. Confirmation policy should reflect the sensor and downstream consequence.
- No new measurement constrains the propagated state, and unmodeled target maneuvers accumulate. Confidence should decrease rather than remain frozen.
- The prediction assumes velocity persists and does not represent the observed deceleration strongly enough. Process noise or an acceleration/turn-aware model may be needed, with validation.
- Logs and consumers may connect separate physical actors into one history. Unique identifiers should be managed with session and lifecycle context.

CHAPTER TAKEAWAY Track management decides when an actor hypothesis is credible, usable, stale, or gone. Motion models and lifecycle rules must be tuned together and evaluated by downstream consequence.

CHAPTER 16 | STATE ESTIMATION

Kalman Filtering and Uncertainty

The Kalman filter is not a noise eraser; it is a recursive argument about what the model and measurement each justify.

Source anchors: R14, R19, R25

LEARNING OBJECTIVES

- Explain prediction, measurement update, innovation, Kalman gain, and covariance in plain and mathematical language.
- Construct a basic linear state-space model with process and measurement uncertainty.
- Diagnose overconfidence, poor tuning, model mismatch, and inconsistent residuals.
- Distinguish linear, extended, unscented, and other filtering approaches without treating one as universal.

Prediction and correction

At each step, a motion model predicts the next state and grows or reshapes uncertainty according to process noise. A measurement model predicts what the sensor should observe from that state. The innovation compares the real measurement with the predicted measurement. The Kalman gain weights the correction according to predicted-state and measurement uncertainty. The updated covariance records the remaining uncertainty under the model assumptions.

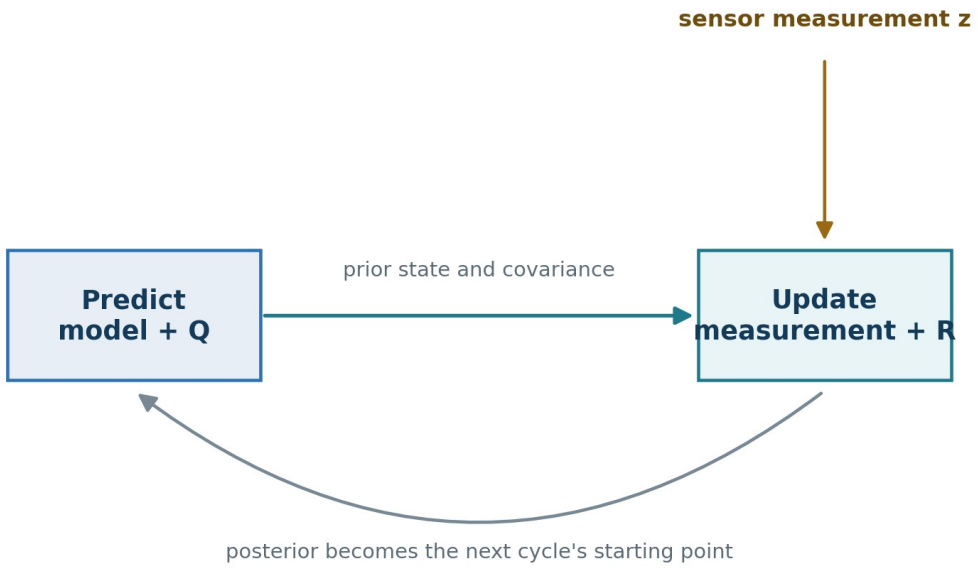


Figure 16.1. Original Project DRIVE predict-update loop with uncertainty propagation and innovation checking.

$$\text{x\_pred} = \text{F x\_prev} + \text{B u} \qquad \text{P\_pred} = \text{F P\_prev F\^{}T} + \text{Q}$$
$$\text{y} = \text{z - H x\_pred} \qquad \text{S} = \text{H P\_pred H\^{}T} + \text{R}$$
$$\text{K} = \text{P\_pred H\^{}T S\^{}-1}$$
$$\text{x\_new} = \text{x\_pred} + \text{K y} \qquad \text{P\_new} = (\text{I - K H})\ \text{P\_pred}$$

Meaning of the matrices

Symbol	Role	Engineering question
x	Estimated state	Which variables are needed, in what frame and units?
F	State transition	Which motion behavior is assumed over the time step?
P	State covariance	How uncertain and correlated are the state components?
Q	Process-noise covariance	Which unmodeled maneuvers or disturbances can occur?
z	Measurement	What did the sensor directly provide and at what time?
H	Measurement model	How should the state appear in measurement space?
R	Measurement-noise covariance	How does sensor uncertainty vary by condition?
y, S	Innovation and its covariance	Is the residual plausible under the stated model?

Table 16.1. Every matrix is an engineering claim that should be reviewable.

If R is made very small, the filter trusts measurements strongly. If Q is made very small, it trusts the motion model strongly. Neither setting creates accuracy by itself. Understated uncertainty can make the filter smooth and confident while wrong; overstated uncertainty can create noisy estimates and large association gates. Tuning should use residual distributions, known scenario categories, sensor specifications where valid, and independent ground truth.

Residual consistency and failure diagnosis

The innovation is a powerful diagnostic signal. Repeated nonzero mean can indicate bias, transform error, latency, or model mismatch. Residuals that grow during turns can expose an inadequate motion model; residuals that change with distance can expose scale or angle error. Abrupt residuals may reflect association changes, outliers, sensor resets, or real maneuvers. Whiteness and normalized-innovation tests help determine whether the stated covariance matches observed behavior.

- Check units, axis conventions, time step, timestamps, and transforms before tuning matrices.
- Plot measurements, predictions, estimates, residuals, and covariance bounds together.
- Partition residuals by range, speed, turn rate, weather, target type, and sensor state.
- Inspect outlier and missed-measurement handling; filtering assumptions often require approximately Gaussian inliers.
- Avoid tuning on the same dataset used for final evaluation.
- Verify numerical stability and positive-semidefinite covariance in the actual implementation.

DEBUGGING ORDER When a filter looks wrong, confirm data meaning, frames, time, association, and model equations before adjusting Q or R. Tuning cannot repair a mislabeled signal.

Nonlinearity and filter choice

The linear Kalman filter assumes linear state transition and measurement relationships with suitable uncertainty models. The extended Kalman filter linearizes nonlinear models around the current estimate using Jacobians. The unscented Kalman filter propagates selected sigma points through nonlinear functions. Particle filters represent distributions using many samples and can model multi-modal beliefs at higher computational cost. The method should match nonlinearity, distribution shape, compute, explainability, and validation evidence.

1. Choose the smallest state that supports the downstream requirement.
2. Write state and measurement models with frames, units, time steps, and assumptions.
3. Start with simulated truth and controlled noise, then add bias, outliers, missed data, and maneuvers.
4. Evaluate estimate error and covariance consistency, not smoothness alone.
5. Compare model alternatives on held-out scenario categories and boundary conditions.
6. Document when the filter declares or should declare that its estimate is not trustworthy.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. A filtered signal is smooth but consistently delayed during braking. Which causes should be examined?
2. What happens when measurement covariance R is unrealistically small?
3. Why is a covariance ellipse not a guaranteed physical containment boundary?
4. Innovation mean shifts only during turns. What hypothesis classes does that pattern support?

Answer notes

- Timestamp/latency, an inadequate constant-velocity model, too little process noise, measurement preprocessing, actuator/reference timing, and association should be checked before simply increasing responsiveness.
- The filter overweights measurements, may follow noise or outliers, shrinks reported uncertainty too strongly, and can create inconsistent gates or confidence.
- It is a statistical representation under the model and distribution assumptions. Bias, non-Gaussian errors, wrong association, model mismatch, or underestimated Q/R can place truth outside more often than expected.
- Turn-model mismatch, yaw/steering ego-state error, extrinsic alignment, time synchronization, nonlinear measurement effects, or turn-correlated association changes are plausible.

CHAPTER TAKEAWAY A Kalman filter is an auditable balance between model and measurement. Its covariance is valuable only when residual evidence shows that the uncertainty claims remain credible across scenarios.

CHAPTER 17 | FUSION AND PREDICTION

Multi-Sensor Fusion, Confidence, and Risk Prediction

Fusion should combine complementary evidence while preserving conflict, correlation, and uncertainty-not average them out of sight.

Source anchors: R14, R15, R16, R19

LEARNING OBJECTIVES

- Compare early, feature-level, object-level, and decision-level fusion architectures.
- Identify correlation, common-cause failure, calibration, timing, and association risks in fusion.
- Explain confidence as a calibrated, context-dependent estimate rather than a universal probability of truth.
- Connect fused tracks to trajectory prediction, collision relevance, and conservative decision behavior.

Where fusion can occur

Early fusion combines low-level or raw-like data after alignment, preserving rich detail but requiring bandwidth, synchronization, and joint processing. Feature-level fusion combines learned or engineered representations. Object-level fusion combines detections or tracks and is easier to modularize, but information discarded upstream cannot be recovered. Decision-level fusion combines function conclusions and can isolate components, though it may hide why sources disagreed.

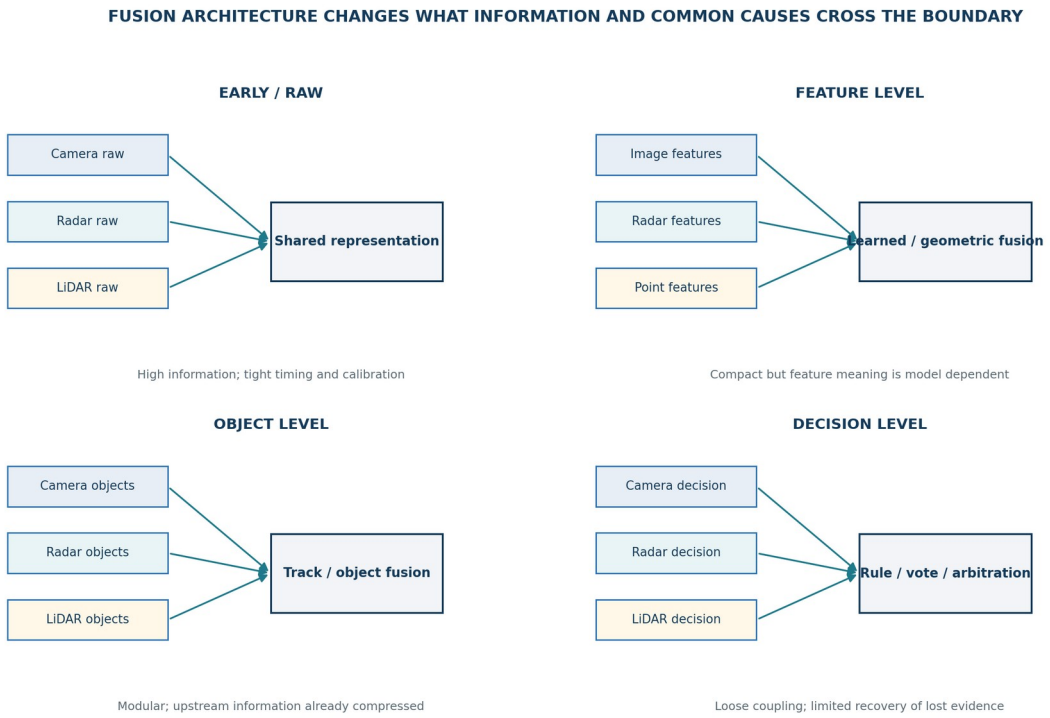


Figure 17.2. Original comparison of early, feature-level, object-level, and decision-level fusion with different information and dependency boundaries.

Fusion level	Advantages	Engineering costs
Raw/early	Rich cross-sensor patterns and shared context	Precise alignment, high bandwidth/compute, coupled training and validation
Feature	Compact learned information	Feature meaning and uncertainty may be difficult to interpret
Detection/object	Modularity, sensor-specific processing, traceable geometry	Association and covariance consistency; upstream information loss
Track-to-track	Independent temporal processing and graceful sensor addition	Correlated priors and double counting are serious risks
Decision	Simple isolation and independent function channels	Late conflict resolution and limited recovery of lost detail

Table 17.1. No fusion level is universally superior; the safety and interface strategy decides.

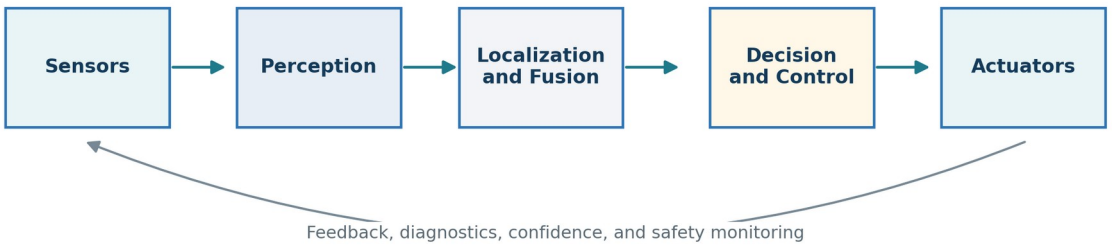


Figure 17.1. Fusion can connect sensing, perception, prediction, and decision at several levels in the system stack.

Correlation and common causes

Combining two estimates as if independent can create false confidence when they share prior information. Two tracks may both use the same vehicle-speed signal, map, time source, or earlier fused estimate. Camera and radar can also share a bracket deformation, power domain, gateway latency, processor, or scenario blind spot. The fusion design needs data-lineage knowledge and explicit common-cause analysis.

- Shared ego state or map prior can correlate otherwise separate sensor estimates.
- Common calibration target or vehicle reference can create aligned bias across sensors.
- A shared compute or gateway can create simultaneous latency, dropout, or reset.
- Training or rule logic can encode the same scenario assumption in several pipelines.
- Environmental causes such as spray, low sun plus wet road, or snow accumulation can affect multiple modalities together.
- Track-to-track fusion should not re-use information that already crossed between the tracks without accounting for it.

MORE SENSORS, MORE TRUTH? Additional sensors increase available evidence, but only architecture, independence analysis, conflict handling, and validation determine whether system confidence should increase.

Conflict and confidence

Suppose radar reports a rapidly closing return and camera reports no vehicle. The absence of a camera detection is not proof of empty road, and the radar return is not proof of a collision object. Fusion should evaluate timestamps, line of sight, camera visibility, radar reflection geometry, track history, ego path, confidence calibration, and sensor health. Depending on risk, the system may preserve separate

hypotheses, lower confidence, request another observation, warn, limit automation, or apply a conservative control policy.

Confidence source	Question before use
Model score	Was it calibrated for this class, range, environment, and software version?
Covariance	Does observed error match the stated distribution and include transform/time uncertainty?
Track history	Is continuity genuine, or could a wrong association be reinforcing itself?
Sensor health	Which faults and limitations can health monitoring detect, and which remain latent?
Cross-sensor agreement	Are the sources independent, aligned, and observing the same physical quantity?
Map/context	Is the contextual prior current, applicable, and capable of being wrong?

Table 17.2. Confidence requires provenance and calibration to a specific use.

Prediction and collision relevance

Prediction estimates how actors and the ego vehicle may evolve over a time horizon. A constant-velocity extrapolation is useful for short baselines but does not represent intent, traffic rules, path geometry, interaction, or multiple plausible futures. Risk prediction should consider occupancy over time, path overlap, uncertainty, braking and steering capability, road friction, response delay, and the consequences of both intervention and non-intervention.

1. Define the decision horizon and which actor states are required.
2. Generate one or more plausible trajectories consistent with map, kinematics, observations, and interaction context.
3. Propagate state, model, map, and timing uncertainty into predicted occupancy.
4. Estimate collision relevance using spatial overlap and time, not TTC alone.
5. Evaluate false-intervention and missed-intervention consequences by scenario.
6. Specify degradation when predictions are multi-modal, unstable, stale, or outside validated coverage.

The correct output may be a distribution over possible futures rather than one trajectory. A pedestrian near a curb might continue, stop, or enter the road. A vehicle at a lane boundary might follow the curve or cut in. Systems that collapse uncertainty too early can behave confidently toward the wrong future. Systems that retain every possibility without prioritization can become unusably conservative. Validation must examine that balance at the vehicle-function level.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. Why can track-to-track fusion become overconfident even when both input covariances look valid?
2. Camera and radar agree on target position. What must be checked before treating agreement as independent confirmation?
3. Why is constant-speed TTC insufficient for a turning or cut-in scenario?

4. What should a fusion system do when sources disagree but neither can be shown wrong?

Answer notes

- The tracks may share priors, ego state, earlier measurements, map information, or cross-fed estimates. Ignoring cross-correlation double-counts evidence.
- Common ego state, calibration reference, timestamps, compute, prior fused data, association, and environmental/common-cause effects must be assessed.
- It ignores lateral path overlap, acceleration, interaction, object extent, multiple futures, uncertainty, and ego-control capability. The scalar can support but not replace scenario geometry.
- Preserve hypotheses and provenance, reduce or bound confidence, seek discriminating evidence if time permits, and move to a function behavior justified by the risk and validated degradation strategy.

CHAPTER TAKEAWAY Fusion is disciplined evidence combination. Its success is measured by calibrated, robust vehicle decisions under agreement, conflict, degradation, and common-cause conditions-not by the number of sensors connected.

PART 4

Functions, Planning, Control, and Software

Chapters 18-21

Connect estimates to behavior, trajectories, shared control, real-time compute, and connected interfaces.

CHAPTER 18 | ADAS FUNCTIONS

ACC, AEB, Lane Support, Blind-Spot, and Parking Functions

Feature names are only the surface; engineering begins with enable criteria, inputs, decisions, outputs, driver role, and safe degradation.

Source anchors: R4, R12, R20, R23

LEARNING OBJECTIVES

- Map common ADAS functions from sensing through driver interface and actuation.
- Distinguish warning, support, and intervention behavior without inventing universal thresholds.
- Explain how enable criteria, inhibition, degradation, and driver override shape observed behavior.
- Connect function performance to realistic scenarios and vehicle-level evidence.

Function maps before feature claims

A camera, radar, ultrasonic array, or ego-state signal may serve several functions, but each function has its own operating conditions, timing, driver interface, and actuation strategy. A forward object track might support adaptive cruise control, forward-collision warning, and automatic emergency braking. The track quality acceptable for comfortable gap control may differ from the evidence required for an emergency intervention. Project DRIVE therefore maps each function separately even when components overlap.

Function	Primary purpose	Typical evidence chain	Critical boundary
ACC	Maintain selected speed/gap	Forward object and ego state -> target selection -> acceleration request	Cut-ins, curves, stopped objects, driver override
FCW/AEB	Warn and/or mitigate certain forward collisions	Object/path/risk estimate -> warning or brake request	False intervention versus missed threat; braking authority
Lane support	Warn or assist lateral position	Lane/path estimate plus vehicle state -> warning/steering request	Marking/road ambiguity, driver steering, curves
Blind-spot/lane-change	Inform about actors in adjacent/rear regions	Side/rear detections -> zone and closing assessment -> indicator/warning	Occlusion, guardrails, motorcycles, rapid approach
Parking support	Assist low-speed proximity or maneuver	Near-field sensing/cameras -> obstacle/free-space estimate -> display/control	Low objects, overhangs, target material, driver observation

Table 18.1. Function summaries are conceptual; exact behavior is vehicle and configuration specific.

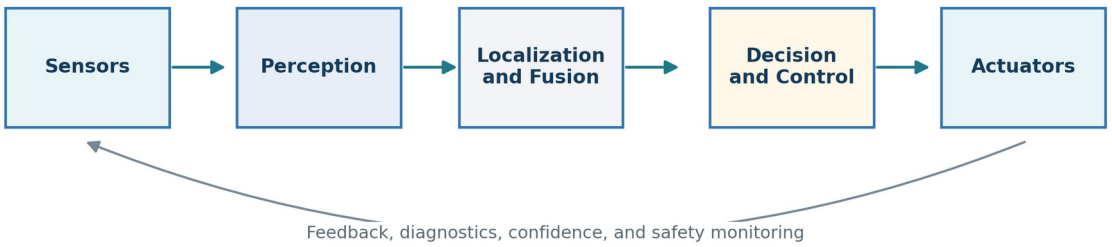


Figure 18.1. Every ADAS feature crosses the same system stack but uses different evidence, authority, and timing.

Longitudinal support: ACC, FCW, and AEB

Adaptive cruise control selects a relevant lead object and regulates speed or gap within its operating conditions. Target selection must understand lane/path relevance: the nearest object is not always the lead vehicle, and a vehicle on a curve may appear laterally offset in the sensor frame. Comfort objectives limit acceleration and jerk, while driver commands, speed limits, actuator capability, and traffic transitions shape behavior.

Forward-collision warning and AEB estimate whether the ego path and an object trajectory create an unacceptable collision risk. They may use time, distance, closing speed, braking estimates, object confidence, driver response, and scenario classification. Warning timing and brake intervention cannot be assigned from a single universal TTC. The design balances available braking distance, false activation risk, driver response, road friction, and object uncertainty under documented requirements.

- Target selection: which object occupies or is entering the ego path?
- Risk estimate: how do relative motion, object extent, path, uncertainty, and response delay combine?
- Driver state: braking, accelerator override, steering, attention, and warning acknowledgment where applicable.
- Vehicle capability: brake availability, stability control, tire-road condition, load, grade, and actuator limits.
- Degradation: which faults or low-confidence conditions disable, limit, or change the function?

Lateral, side, and low-speed support

Lane-departure warning evaluates vehicle position and motion relative to a lane or road boundary. Lane-keeping assistance adds steering support, while lane-centering provides more sustained lateral guidance within feature conditions. The system must handle intentional lane changes, driver steering torque,

missing markings, splits, merges, shoulders, construction, and curves. A visible lane is not necessarily an unambiguous drivable path.

Blind-spot and lane-change support use side/rear sensing and track logic to evaluate zone occupancy and approach. Zone geometry depends on vehicle reference, trailer or body configuration where supported, and sensor alignment. Parking systems operate at low speed with short ranges but face strong geometric challenges: poles, curb edges, children, overhangs, reflective or absorbent surfaces, camera occlusion, and rapidly changing steering geometry.

WARNING VERSUS GUARANTEE A warning system's lack of an alert does not prove the path is clear. Feature documentation, driver responsibility, sensing coverage, object type, geometry, and operating conditions determine what the absence means.

Feature behavior as a state machine

Observed feature behavior is easier to explain as states and transitions: unavailable, available, armed, active, warning, intervention, overridden, degraded, faulted, or cooling/temporary-limited. Each transition has conditions and priority. A driver may see the same icon for different internal reasons, so diagnostic records should capture state signals, prerequisites, inhibition reason, DTC context, and scenario conditions.

1. Identify the exact feature and authoritative operating description.
2. List enable, inhibit, override, cancel, fault, and recovery conditions.
3. Trace sensor, ego-state, network, driver-input, and actuator dependencies.
4. Define observable outputs for each state: telltales, messages, data, requests, and logs.
5. Create boundary scenarios near speed, visibility, curvature, target, and driver-input limits.
6. Verify transition timing and safe degradation, not only steady-state success.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. Why may an ACC system ignore a closer object that is outside the predicted ego path?
2. A lane icon is visible but steering support does not activate. What state-machine evidence is needed?
3. Why is an AEB false activation not simply the opposite of a missed detection?
4. A blind-spot indicator is quiet beside a stationary roadside object. Which questions determine whether that is expected?

Answer notes

- Relevance depends on lane/path association, object trajectory, road curvature, and feature logic. Pure range does not define the lead target.

- Feature availability, lane confidence, speed, driver input, turn signal, hands/attention conditions where applicable, stability-control state, faults, and inhibition reason should be captured.
- False activation can result from real detection with wrong path relevance, association, prediction, map/ego state, decision threshold, or actuator command. Missed detection is only one different failure class.
- Check the designed zone, motion/closing criteria, object type and geometry, sensor coverage, operating speed, feature state, environment, and vehicle-specific documentation.

CHAPTER TAKEAWAY ADAS functions are stateful vehicle behaviors built from shared but differently qualified evidence. Evaluate enable logic, relevance, transitions, driver role, and degradation-not just whether a sensor can see something.

CHAPTER 19 | PLANNING AND DECISION MAKING

Behavior Planning, Motion Planning, and Trajectory Generation

Planning turns an uncertain scene into a feasible, lawful, comfortable, and continuously revisable motion proposal; it does not merely draw a line around obstacles.

Source anchors: R15, R27, R28, R32, R38

LEARNING OBJECTIVES

- Separate mission, route, behavior, motion, trajectory, and control responsibilities.
- Distinguish a geometric path from a time-parameterized trajectory and a control command.
- Compare search, sampling, lattice, optimization, and model-predictive approaches at a conceptual level.
- Explain feasibility, cost, constraints, prediction uncertainty, collision checking, and replanning.
- Build validation evidence for planning decisions, fallback, comfort, and interactions with other road users.

The planning hierarchy

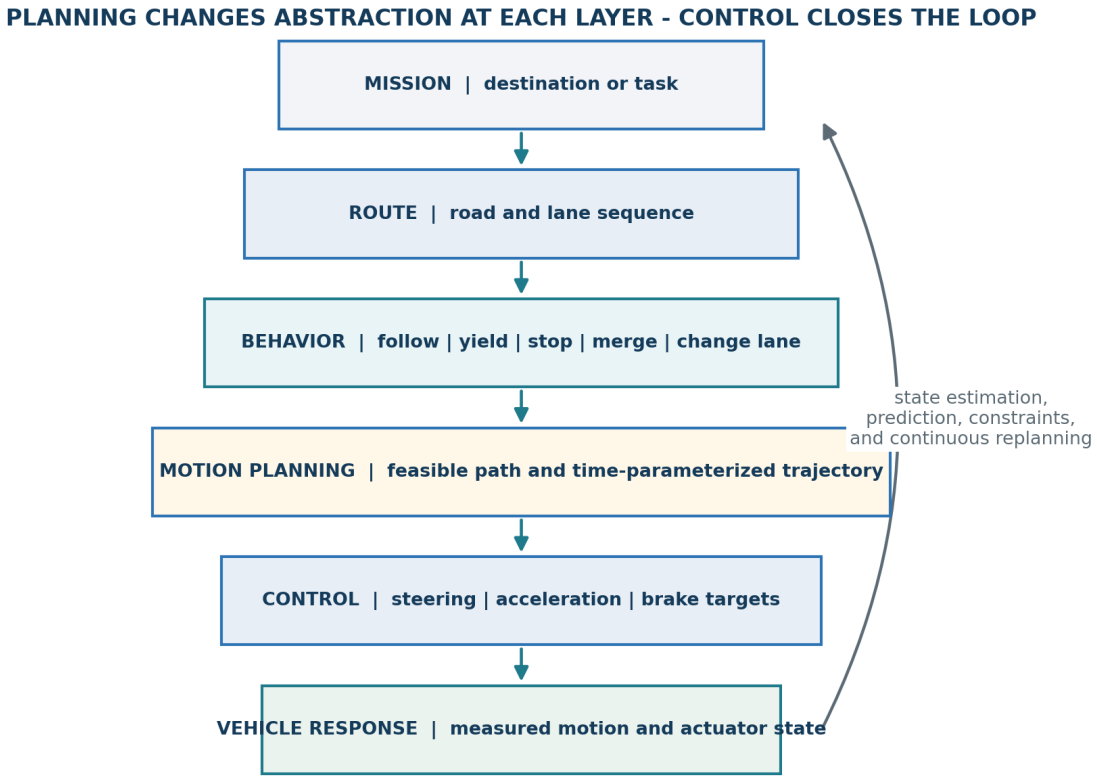


Figure 19.1. Original planning hierarchy from mission and route through behavior, candidate trajectories, control targets, and vehicle response with continuous feedback.

Mission planning defines the destination or task. Route planning selects a road-network path. Behavior planning selects a tactical action such as follow, yield, stop, merge, change lane, or remain in lane. Motion planning proposes a collision-free and dynamically feasible path or trajectory. Control then converts the selected trajectory into steering, brake, propulsion, and other actuator requests. Real systems may divide the work differently, but each decision still needs a clear input contract, output contract, authority boundary, and timing budget.

Layer	Primary question	Typical output	Failure example
Mission	What task is requested?	Destination or service objective	Ambiguous or unauthorized destination
Route	Which road sequence is suitable?	Lane/road-level route	Closed or incompatible road remains selected
Behavior	What tactical maneuver is appropriate?	Yield, follow, stop, merge, lane change	Oscillation between competing states
Motion	How can the maneuver be executed?	Path or time-parameterized trajectory	Geometric clearance but infeasible curvature
Control	Which actuator request follows the trajectory?	Steering, acceleration, brake targets	Delay or saturation destabilizes tracking

Table 19.1. Planning layers operate at different abstractions but share one vehicle-level safety boundary.

Path, trajectory, feasibility, and constraints

A path describes geometric position or pose along a route. A trajectory adds time and therefore speed, acceleration, jerk, and the timing of interaction with moving actors. A path can be collision-free as a static curve but unsafe as a trajectory if the vehicle arrives when another actor occupies the same space. A trajectory can also be geometrically clear but physically infeasible because curvature, tire force, steering rate, braking, power, or actuator delay limits are exceeded.

$$\text{trajectory } q(t) \text{ must satisfy state, input, road, collision, and comfort constraints}$$
$$\text{curvature approximately equals yaw\_rate / speed when speed is nonzero}$$
$$\text{stopping\_distance includes reaction and system delay plus braking distance}$$
$$\text{cost} = w_{\text{progress}} J_{\text{progress}} + w_{\text{risk}} J_{\text{risk}} + w_{\text{comfort}} J_{\text{comfort}} + w_{\text{rules}} J_{\text{rules}} + \ldots$$

Constraints define what is prohibited or required: remain within a drivable corridor, avoid predicted occupancy, respect steering and acceleration limits, preserve a safety margin, and stop before a limit line. Costs rank feasible alternatives: progress, comfort, clearance, energy, lane preference, and stability of behavior. A large penalty is not always equivalent to a hard constraint. If collision avoidance is represented only as a finite cost, an optimizer may accept collision when other weighted objectives become numerically larger.

CONSTRAINT DISCIPLINE Write down which conditions are inviolable, which may be relaxed under a defined emergency strategy, and which are preferences. Hidden conversion between a safety constraint and a tunable cost is a critical design decision.

Search, sampling, lattices, and optimization

Graph search explores connected states or road segments using costs and heuristics. Sampling-based methods explore continuous configuration or state space and are useful when geometry and motion constraints make a regular grid expensive. Lattice planners evaluate a structured library of dynamically meaningful motion primitives. Optimization methods adjust a path or trajectory to minimize cost while satisfying constraints. Many vehicle planners combine approaches: a behavior state narrows the problem, a lattice generates candidates, collision checks reject invalid choices, and optimization smooths the selected result.

Approach	Useful when	Watch for
Graph search	The state or road network has useful discrete structure	Resolution, heuristic bias, and state explosion

Approach	Useful when	Watch for
Sampling based	Continuous spaces and complex constraints are difficult to grid	Narrow passages, convergence time, and path quality
Lattice / motion primitives	Vehicle-feasible candidates can be prestructured	Library coverage and discontinuities between primitives
Trajectory optimization	Smooth costs and constraints can be solved fast enough	Local minima, initialization, scaling, and solver failure
Model predictive control	Optimization can repeat as feedback over a moving horizon	Compute deadline, model mismatch, horizon, and terminal behavior

Table 19.2. Planning methods trade completeness, structure, computation, and explainability.

Model predictive control repeatedly estimates the current state, solves a finite-horizon trajectory or control problem, applies the first portion, and solves again after new evidence arrives. This makes it responsive to disturbance and prediction change, but it also makes solver timing, warm starts, constraint feasibility, and fallback behavior part of the control loop. A mathematically elegant solution that misses its deadline is not a valid real-time solution.

Prediction, interaction, and uncertainty

Planning depends on predictions of other actors, yet those actors react to the ego vehicle and may have several plausible goals. A vehicle at a lane boundary may continue straight, merge, or yield. A pedestrian may cross, wait, or step back. Representing only the most likely future can produce unsafe overconfidence. Representing every physically possible future can make the vehicle unable to move. The planning policy therefore needs a documented treatment of probability, severity, uncertainty growth, occlusion, and controllability.

- Multimodal prediction preserves several plausible futures rather than one average trajectory.
- Interaction-aware planning recognizes that the ego maneuver can change another actor's future behavior.
- Risk-sensitive planning weights probability together with consequence and available mitigation.
- Occlusion-aware planning treats hidden emergence zones as uncertain rather than empty.
- Contingency planning preserves an alternate response when the preferred plan becomes invalid.

Safety margins should reflect localization, shape, timing, prediction, and control error instead of using one universal buffer. Enlarging every object equally can create unnecessary stops and new interaction risk. The correct margin may depend on closing speed, actor vulnerability, road geometry, escape options, sensor coverage, and braking authority. The reasoning must remain inspectable even when numerical optimization performs the final selection.

Rules, comfort, courtesy, and explainability

A technically feasible trajectory can still be poor driving. It may violate a traffic rule, cut too close to a cyclist, block an intersection, accelerate toward a red light, or oscillate between lane positions. Comfort

limits on acceleration and jerk are not cosmetic; harsh motion can reduce controllability, surprise occupants and nearby road users, and destabilize perception. Courtesy and social expectations are context-dependent and must not override explicit safety constraints.

Explainability at the planning level does not require every optimization variable to be shown to a driver. Engineers need traceable reasons: the selected behavior state, rejected candidates, active constraints, risk terms, map and signal evidence, predicted actor modes, and the trigger for replanning or fallback. These records make scenario review and safety analysis possible without pretending the entire decision is reducible to one sentence.

Replanning, fallback, and validation

Planning is continuous. New measurements, localization updates, map changes, actuator limits, and other actors can invalidate the current trajectory. The planner needs a stable update rhythm, a safe way to hand a new trajectory to control, and protection against rapid oscillation. If no acceptable trajectory is found, the system must enter a defined degraded or fallback strategy based on its automation responsibility and ODD. Reusing the last trajectory without checking freshness can be more dangerous than reporting planner failure.

1. Specify the behavior decision, maneuver constraints, planning horizon, update rate, and control handoff.
2. Test nominal, boundary, adversarial, and infeasible cases with time-aligned ground truth and internal decision logs.
3. Vary prediction modes, localization error, friction, actuator delay, occlusion, map error, and compute load.
4. Measure collisions, rule violations, clearance, progress, comfort, stability, intervention, fallback, and deadline misses.
5. Replay failures across software-in-the-loop, hardware-in-the-loop, simulation, proving-ground, and controlled vehicle tests as appropriate.
6. Trace every pass criterion to a requirement and every unexplained behavior to a reviewed limitation or corrective action.

SCENARIO STANDARDS ASAM OpenSCENARIO and related OpenX specifications can support interoperable scenario and road descriptions, while ISO 34502 provides public scope for scenario-based ADS safety evaluation. Formats organize evidence; they do not choose coverage or prove that a simulator is sufficiently faithful.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. A geometric path clears every obstacle, but the vehicle cannot follow its curvature at the planned speed. Which planning distinction was missed?
2. Why can one average predicted trajectory for another vehicle be less safe than several plausible modes?
3. An optimizer finds a low-cost trajectory that slightly violates a collision boundary. What design question should be asked first?
4. A planner produces excellent trajectories but occasionally finishes after the control deadline. Is the planner acceptable?
5. What should happen when no feasible trajectory is available and the current trajectory is becoming stale?

Answer notes

- Geometric collision freedom was confused with dynamic feasibility. Speed, curvature, tire force, steering rate, and actuator limits must be checked in a time-parameterized trajectory.
- A mean can fall between real intentions and under-represent both. Multiple modes or a probability field preserve the actual alternatives for risk assessment.
- Determine whether the boundary is intended as a hard safety constraint or only a weighted preference. A finite penalty may permit violation when other costs dominate.
- Not without a timing and fallback argument. Deadline misses are functional failures because control acts on stale or missing targets, regardless of offline trajectory quality.
- Activate the defined fallback or minimum-risk strategy appropriate to system responsibility, freshness, vehicle state, and available control authority. Do not silently continue a stale plan.

CHAPTER TAKEAWAY Planning is a real-time safety-relevant decision process under uncertainty. Separate path from trajectory, preference from constraint, and mathematical optimality from feasible, timely, explainable vehicle behavior.

CHAPTER 20 | VEHICLE INTEGRATION AND CONTROL

Control Interfaces, Actuators, Driver Interaction, and Arbitration

A correct perception estimate can still create poor vehicle behavior if control authority, timing, actuator limits, or human interaction are misunderstood.

Source anchors: R6, R13, R21, R24, R37

LEARNING OBJECTIVES

- Describe the progression from behavior decision to trajectory, control request, actuator response, and vehicle motion.
- Explain feedback control, feedforward, error, gain, stability, saturation, and jerk at a working level.
- Analyze command arbitration among driver, ADAS, stability control, propulsion, braking, and fail-safe logic.
- Connect driver monitoring, mode awareness, override, and transition design to system safety.

From intent to motion

A decision such as 'increase following distance' must become a target trajectory or acceleration, then a controller request, actuator command, and measured vehicle response. Feedback compares the desired state with the observed state and corrects error. Feedforward uses a model to anticipate the command required. Real systems combine both and must respect actuator delay, saturation, rate limits, friction, powertrain state, braking availability, tire forces, and comfort constraints.

$$\text{control\_error } e(t) = \text{desired\_output} - \text{measured\_output}$$

$$\text{proportional action } u\_P = K\_P\, e$$

$$\text{PI/PID concepts add accumulated error and rate-of-change terms where appropriate}$$

$$\text{jerk} = \text{change in acceleration} / \text{time}$$

Control concern	Vehicle symptom	Evidence
Delay	Late response or oscillation	Command/actual timestamps, network and actuator latency
Saturation	Target cannot be reached	Command limit, brake/torque availability, friction, thermal state
Gain/model mismatch	Overshoot, hunting, sluggish response	Error history, speed/load/road partitions, controller version
Sensor bias	Persistent offset or steering pull	Independent reference, alignment, state-estimate residuals

Control concern	Vehicle symptom	Evidence
Mode transition	Unexpected step in torque or steering	State transition, integrator state, handoff and ramp logic

Table 20.1. Control diagnosis compares requested and achieved behavior through time.

Longitudinal and lateral interfaces

Longitudinal control may request acceleration, wheel torque, brake pressure, deceleration, or a coordinated motion target through a chassis controller. Propulsion and brake blending, regenerative braking, grade, load, and traction limits affect realized deceleration. Lateral control may request steering angle, steering torque, curvature, or path tracking through an electric power steering interface. Steering ratio, compliance, tire behavior, speed, and road bank affect the result.

- Command definition: physical quantity, sign, unit, reference point, rate, and validity.
- Authority: maximum magnitude, duration, ramp, and conditions allowed for the requesting function.
- Response feedback: actual torque/pressure/angle, status, limitation, fault, and achieved motion.
- Timing: request cycle, timeout, end-to-end latency, stale-data behavior, and synchronization.
- Fallback: behavior when the actuator rejects, limits, or cannot achieve a request.
- Verification: compare intent, request, actuator response, and vehicle dynamics in one aligned trace.

Arbitration and driver authority

Several systems can request motion simultaneously: the driver, ACC, AEB, lane support, stability control, traction control, parking assistance, powertrain protection, and fail-safe logic. Arbitration defines priority and combination rules. Emergency braking may override comfort cruise control; stability control may reshape a request; driver accelerator or steering input may cancel or override some features but not every safety intervention. These policies are vehicle specific and safety analyzed.

Interaction	Engineering questions
Driver override	Which input, magnitude, duration, and state cancels or modifies automation?
Competing requests	Which function has priority, and can requests be safely blended?
Actuator limitation	How is reduced capability reported and propagated to the requesting function?
Fault/degradation	What control authority remains, and how is the driver informed?
Recovery	Does the system resume automatically, remain unavailable, or require deliberate re-engagement?

Table 20.2. Arbitration should be testable as states, priorities, and transitions.

HUMAN-CENTERED BOUNDARY A technically stable controller can still be unsafe if the driver misunderstands the mode, does not perceive a transition, or cannot provide the expected fallback. Interface design is part of the control system.

Driver monitoring and mode awareness

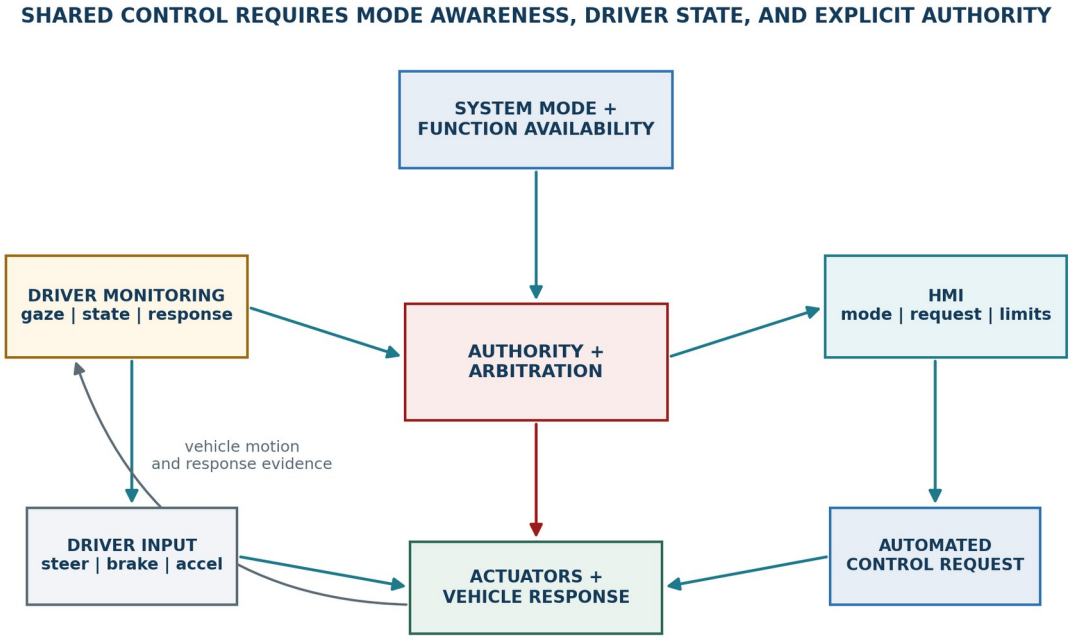


Figure 20.1. Original shared-control loop connecting system mode, driver monitoring, HMI, driver input, arbitration, actuators, and vehicle response.

Driver-support systems depend on appropriate human supervision. Driver monitoring may use steering interaction, gaze/head pose, eyelid behavior, or other indicators depending on design. These are estimates with uncertainty and privacy implications, not direct access to intent. Alerts and escalation should be validated for false warnings, misses, accessibility, lighting, eyewear, posture, and cultural or demographic variation where relevant.

1. Define the driver's role in each system state and transition.
2. Identify what the system can actually observe about driver engagement and its limitations.
3. Make mode, availability, request, limitation, and disengagement distinguishable through the interface.
4. Test driver override, delayed response, no response, confusion, and unexpected system degradation.
5. Measure vehicle behavior and human response together instead of validating the controller alone.
6. Protect monitoring data and restrict its use to authorized, documented purposes.

Transitions, driver state, and calibrated trust

A transition of control is a time-dependent system state, not merely a chime or message. The driver must perceive the request, understand the mode and reason, reorient to the roadway, decide, and produce a usable response. Vehicle dynamics and available time continue changing during that

sequence. A takeover strategy must therefore connect detection, HMI, driver-state evidence, control authority, fallback, and the conditions under which the system concludes that the driver has or has not resumed the required role.

Driver-monitoring systems can estimate gaze, eyelid behavior, head pose, hand engagement, impairment indicators, or response, but their coverage varies with glasses, lighting, seating, facial features, occlusion, culture, disability, and behavior. A steering-wheel torque signal is not equivalent to attention. Euro NCAP's current Safe Driving material separates occupant monitoring, driver engagement, and vehicle assistance concerns, reinforcing the need to evaluate both detection and the vehicle response.

TRUST CALIBRATION The HMI should help the driver form an accurate belief about what the system is doing, what it sees, what it requires, and what it cannot do. Too little trust causes disuse; too much trust encourages misuse and delayed intervention.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. A controller requests strong deceleration, but the vehicle response is weak. Which interfaces and physical limits must be reviewed?
2. Why can a stable lane-centering controller still produce poor driver experience?
3. Two ECUs request opposite steering torques. What evidence defines correct behavior?
4. How can network latency destabilize a feedback loop even when every signal value is numerically correct?

Answer notes

- Trace risk decision, requested quantity, arbitration, brake/propulsion response, achieved pressure/torque, friction, grade/load, thermal/traction limits, faults, and synchronized timestamps.
- It may create high steering effort, frequent mode changes, poor centering preference, unclear override, uncomfortable jerk, or confusing interface states. Human interaction is a requirement set of its own.
- The authorized arbitration and safety concept define priority, blending, rejection, driver override, and fallback. Observe requests, state, output, limitation flags, and vehicle response against those requirements.
- Delay adds phase lag: the controller reacts to an old state, may overcorrect, and can oscillate. End-to-end timing belongs in stability analysis.

CHAPTER TAKEAWAY Vehicle control is an end-to-end timed loop that includes driver interaction and competing authorities. Validate desired motion, requested action, actuator response, actual vehicle behavior, and transitions together.

CHAPTER 21 | SOFTWARE AND COMPUTE PLATFORMS

Real-Time Software, Compute Platforms, and Connected Interfaces

Correct output delivered too late, with the wrong version, in the wrong frame, or through an untrusted interface is still incorrect system behavior.

Source anchors: R18, R30, R31, R34, R35, R36, R41, R42, R43

LEARNING OBJECTIVES

- Explain tasks, processes, scheduling, latency, jitter, deadlines, determinism, and watchdogs at a working level.
- Describe message contracts, quality of service, timestamps, buffering, and backpressure in a distributed ADAS/ADS stack.
- Relate CPU, GPU, accelerators, memory, thermal limits, and power integrity to end-to-end function timing.
- Compare signal-oriented, service-oriented, domain, zonal, and central-compute concepts without treating one architecture as universally superior.
- Connect configuration, Automotive SPICE, logging, updates, cybersecurity, and V2X trust to lifecycle evidence.

Real time means bounded timing

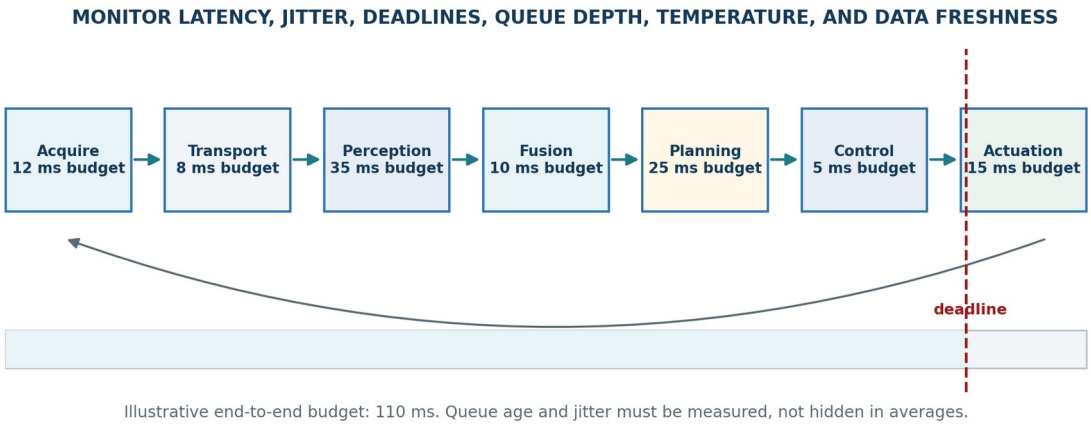


Figure 21.1. Original end-to-end timing budget showing acquisition, transport, compute, fusion, planning, control, and actuation with latency, jitter, and deadline monitoring.

A real-time system is designed so important actions complete within bounded timing constraints. Latency is elapsed time from cause to usable response. Jitter is variation in that time. A deadline is the latest acceptable completion time for a task or end-to-end chain. Throughput is the amount of work completed per interval. A system can have high throughput and low average latency while rare scheduling, memory, network, or thermal events create unacceptable deadline misses.

$$\text{end\_to\_end\_latency} = \text{acquisition} + \text{queueing} + \text{transport} + \text{compute} + \text{fusion} + \text{planning} + \text{control} + \text{actuation}$$

$$\text{age\_of\_information at use} = \text{current\_time - measurement\_timestamp}$$

$$\text{deadline\_margin} = \text{allowed\_time - worst\_relevant\_completion\_time}$$

Timing term	Question	Vehicle consequence
Latency	How old is evidence when acted upon?	Object or lane position is spatially stale
Jitter	How much does delay vary?	Tracking and control receive irregular updates
Deadline miss	Was the result too late to use?	Stale plan, skipped control cycle, or degraded mode
Throughput	Can the platform sustain the required workload?	Queues grow and age even when individual tasks are fast
Determinism	Are relevant timing and ordering behaviors bounded?	Rare sequences escape average-case testing

Table 21.1. Timing evidence must connect platform behavior to vehicle consequence.

Tasks, scheduling, memory, and health monitoring

A process provides an execution and memory boundary; threads or tasks perform work within scheduling rules. Priorities, periods, event triggers, locks, interrupt handling, and shared resources shape timing. Priority inversion occurs when a high-priority task waits on a resource held by lower-priority work. Unbounded memory allocation, page faults, blocking input/output, logging bursts, and cache contention can create rare delay. Real-time design limits or measures these effects instead of assuming they will average out.

- Watchdogs detect missing progress but need a safe response and protection against false resets.
- Heartbeats show that a component is alive, not that its output is correct, timely, or semantically valid.
- Deadline monitors should identify the affected data and downstream consumer, not only a CPU percentage.
- Resource monitors need thresholds for memory, queue depth, temperature, power, storage, and accelerator availability.
- Degraded modes should be designed and verified before overload occurs, with explicit authority and recovery conditions.

ROS 2 documentation distinguishes ordinary performance from real-time programming concerns and emphasizes avoiding nondeterministic operations in critical paths. ROS 2 is a valuable learning and prototyping environment, but using it does not automatically create an automotive-qualified platform.

Middleware behavior, operating system, drivers, allocator, network, hardware, safety mechanisms, and development process all contribute to the deployed system.

Messages, services, quality of service, and time

Distributed components exchange signals, messages, streams, or services. Every interface needs units, coordinate frame, timestamp meaning, update rate, valid range, uncertainty, sequence behavior, timeout, and degraded semantics. A field named speed is incomplete until the frame, sign, units, source, filtering, and time are defined. Compatibility also includes schema version and whether old and new producers can coexist safely.

Interface property	Failure if unspecified
Timestamp origin	Transport time is mistaken for measurement time
Frame and units	Numerically plausible values describe different geometry or scale
Reliability policy	Critical state is dropped or stale samples accumulate
Queue depth	Burst traffic creates hidden age and memory growth
Ordering and sequence	Late samples overwrite newer state or tracks regress in time
Timeout and validity	A consumer continues using data after the producer is impaired
Schema/version	Meaning changes while fields still deserialize successfully

Table 21.2. An interface contract includes meaning, timing, and failure behavior.

Quality-of-service choices control reliability, history, durability, deadlines, and liveliness in some middleware. More reliability can increase delay or queueing when the network is impaired. A latest-value control state may need a different policy from an audit log that must not lose events. Backpressure occurs when a producer outpaces a consumer; the system must choose whether to block, drop, decimate, or degrade rather than allow unbounded stale data.

Compute hardware, acceleration, power, and thermal limits

CPUs are flexible for control flow and general computation. GPUs and dedicated accelerators provide parallel throughput for matrix, image, or point-cloud operations. Memory bandwidth and data movement can limit performance even when arithmetic capacity is high. Copying a large tensor among camera, CPU, GPU, and another process can consume more time and power than expected. Zero-copy and shared-memory designs reduce movement but increase lifetime, ownership, and isolation complexity.

Temperature, supply voltage, power budget, clock scaling, and hardware faults can change execution time or availability. A benchmark on an open laboratory platform does not prove worst-case performance inside a hot vehicle after hours of operation. Validation should combine realistic sensor load, concurrent tasks, logging, network traffic, storage activity, thermal soak, power transients, and fault injection. The metric is end-to-end function behavior, not only accelerator utilization.

PLATFORM BOUNDARY A model benchmark measured without preprocessing, transport, synchronization, postprocessing, and concurrent vehicle workload is not an end-to-end timing result.

From distributed ECUs to service-oriented platforms

Traditional distributed architectures place functions across many dedicated ECUs and signal-oriented networks. Domain architectures consolidate related functions such as chassis, body, or ADAS. Zonal architectures group physical input/output by vehicle location and connect zones to central compute. Centralized platforms consolidate high-performance computation while remote controllers preserve local sensing and actuation. Actual vehicles combine patterns; physical safety, wiring, latency, cost, redundancy, serviceability, and upgrade strategy shape the result.

Service-oriented communication lets applications discover and call defined services instead of relying only on fixed signal routes. AUTOSAR Adaptive Platform provides service and API concepts for adaptive applications, while AUTOSAR Classic remains important for deeply embedded control. An architecture label does not prove safety or flexibility. Engineers still need deterministic boundaries, network protection, version compatibility, health management, and a safe response when a service disappears or returns incompatible data.

Configuration, development process, logging, and updates

Configuration is part of function identity: software build, calibration dataset, model, map, feature coding, network schema, hardware revision, diagnostic dataset, and update history. Automotive SPICE defines process reference and assessment models for evaluating development processes; it does not certify that a particular feature is safe. Its value for a learner is the discipline of requirements, architecture, implementation, integration, verification, configuration management, change control, and objective evidence.

1. Assign immutable identifiers to software, model, data, calibration, map, and interface versions.
2. Trace each requirement to architecture, implementation, test, result, anomaly, and approval status.
3. Capture logs with a time base, configuration manifest, data-validity status, and privacy controls.
4. Evaluate the update package, dependencies, compatibility, security, power conditions, installation state, and rollback path.
5. Run targeted and system-level regression after updates, including changed timing, resource use, and degraded behavior.
6. Monitor field anomalies and decide when evidence requires investigation, containment, rollback, or a new release.

UNECE Regulations 155 and 156 provide regulatory frameworks for cybersecurity management and software-update management in applicable markets. ISO 24089 addresses software-update engineering

across organizations, projects, ECUs, vehicles, and supporting infrastructure. Their public scope reinforces a core systems lesson: an update is an engineered lifecycle event, not simply a new binary transferred to a vehicle.

V2X and external information as untrusted evidence

Vehicle-to-everything communication can exchange information among vehicles, infrastructure, and other road users. It can extend awareness beyond direct line of sight and support warnings about traffic signals, sudden braking, work zones, vulnerable road users, or hazards. It also introduces external time, position, identity, credential, availability, privacy, and cybersecurity dependencies. A received message is evidence with provenance and freshness; it is not unquestioned ground truth.

V2X check	Reason
Authentication and authorization	A valid radio message must come from an authorized, trusted role
Freshness and sequence	Replayed or delayed data can be validly signed but operationally wrong
Position and time uncertainty	Sender localization error propagates into the receiver's scene
Plausibility and consistency	External claims should be compared with onboard sensing and map context
Availability and fallback	Loss of coverage must not remove a required onboard safety capability unexpectedly
Privacy and retention	Identifiers and movement data need controlled collection, access, and storage

Table 21.3. Connected information expands awareness and the trust boundary together.

CONNECTED-SYSTEM RULE Treat external data as a time-bounded, attributable measurement. Define how the vehicle behaves when it is absent, conflicting, implausible, compromised, or newer than the onboard map but older than the current scene.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. A perception task averages 20 ms but occasionally takes 120 ms. Which timing evidence is still missing?
2. A heartbeat is present from the planning process. What does it fail to prove?
3. Why can a reliable message-delivery policy make a control consumer less safe during network impairment?
4. A neural-network accelerator is faster in isolation after an update. Which system-level regressions remain possible?
5. A signed V2X message reports a stopped vehicle ahead. Why must the receiver still check freshness, position uncertainty, and plausibility?

Answer notes

- The relevant worst-case or high-percentile completion time, cause of outliers, deadline, end-to-end age, queue behavior, resource/thermal conditions, and safe response to a miss are missing.
- It proves only that some liveness signal arrived. It does not prove correct inputs, timely computation, valid output, safe internal state, or successful downstream delivery.
- Retransmission and queueing can preserve every old sample while increasing age. Latest-state control may need stale samples dropped rather than delivered late.
- Pre/postprocessing, memory transfers, concurrency, temperature, power, numerical precision, queueing, output ordering, model compatibility, and end-to-end deadlines can all regress.
- The sender can have localization error; a valid message can be delayed or replayed; and scene conditions can change. Authentication addresses origin, not complete operational truth.

CHAPTER TAKEAWAY Software architecture, compute, networks, configuration, updates, and connected data are part of the vehicle function. Verify semantic correctness and bounded timing together, across the complete lifecycle.

PART 5

Calibration, Validation, and Safety Assurance

Chapters 22-24

Build traceable evidence across service information, scenarios, verification, AI assurance, cybersecurity, and field evolution.

CHAPTER 22 | CALIBRATION AND SERVICE VERIFICATION

Calibration Evidence and Responsible Composite-Vehicle Navigation

Calibration is a controlled relationship among sensor, vehicle, target, environment, software, and procedure-not a button press or a universal repair rule.

Source anchors: R1, R2, R3, R11

LEARNING OBJECTIVES

- Separate calibration, aiming, initialization, programming, coding, and learning operations.
- Build a procedure-first calibration readiness and evidence packet.
- Explain static, dynamic, and combined calibration concepts without substituting generic steps for OEM instructions.
- Use the ASE Composite Vehicle Type 1 booklet as a reference-navigation exercise without reproducing protected content.

Triggers are researched, not memorized universally

Calibration requirements vary by vehicle, option content, sensor, software, repair, collision event, glass/body operation, alignment condition, and market. Similar-looking models can have different triggers and tools. A technician or engineer should identify the exact vehicle and system, retrieve current OEM information, document the source and revision, and then determine prerequisites and authorized steps.

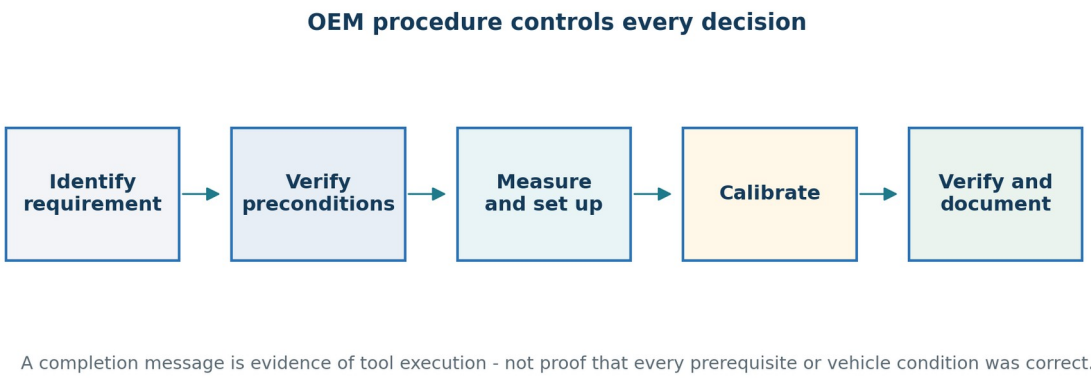


Figure 22.1. Original calibration evidence workflow from procedure research through readiness, execution, and independent verification.

Operation	Working distinction
Inspection/measurement	Documents physical condition or geometry; does not necessarily change a parameter
Mechanical aiming	Physically changes a sensor or lamp orientation according to a specification
Initialization	Establishes an initial state, reference, or learned starting condition
Programming/coding	Changes software or configuration; not a physical alignment process
Calibration	Establishes or corrects a defined measurement/reference relationship
Dynamic learning	Uses specified driving/environment conditions to estimate or confirm parameters

Table 22.1. Exact terminology follows OEM information; the distinctions prevent incomplete documentation.

Readiness before execution

Static calibration commonly uses a stationary vehicle, controlled geometry, and specified targets or fixtures. Dynamic calibration commonly uses prescribed driving conditions and environmental features. Some systems use both. The labels do not define interchangeable steps. Target dimensions, distances, floor slope, lighting, surrounding reflections, wheel alignment, tire pressure, ride height, loading, steering position, battery support, software state, and scan-tool version may be relevant only as the exact procedure states.

- Vehicle identification, option/build information, sensor part and software/configuration state.
- Repair history and the specific operation that triggered procedure research.
- Current OEM procedure source, document identifier/revision, and access date.
- Pre-scan, related DTCs, battery support, communication, and prerequisite module states.
- Tires, suspension, ride height/loading, alignment, body/glass/mounting condition where required.
- Bay geometry, floor, lighting, space, target/tool identification and current verification status.
- Measured setup values, screenshots or records, completion message, post-scan, and prescribed verification.

STOP CONDITION If a prerequisite cannot be established or the environment cannot meet the procedure, pause and document the gap. Repeating the routine does not convert an uncontrolled setup into valid evidence.

Completion is not the entire proof

A controller's successful completion message proves that its internal routine accepted the provided conditions and data according to its logic. It does not independently certify target placement, floor geometry, unreported vehicle damage, tool accuracy, every software configuration, or performance in the full operating domain. Verification therefore connects procedural evidence with diagnostic state and prescribed function checks.

1. Retain the exact procedure and prerequisite record used.

2. Record setup measurements and tool/target identification before running the routine.
3. Capture completion status, relevant learned values or results where available, and any warnings.
4. Perform the required post-scan and resolve or document remaining diagnostic conditions.
5. Complete OEM-prescribed static, dynamic, or road verification safely and legally.
6. Check related functions and compare evidence with the original concern; state remaining limitations.

A post-calibration road drive should not become an uncontrolled test of emergency intervention. Use manufacturer-defined confirmation methods and workplace safety controls. Production-system thresholds, activation boundaries, and test equipment requirements must not be guessed or provoked on public roads.

Using the ASE Composite Vehicle responsibly

ASE's official Composite Vehicle Type 1 booklet describes a fictional composite vehicle created for reference during the L4 certification process. It is not a production model and it does not replace OEM service information. Its educational value for Project DRIVE is navigation: readers can practice identifying system descriptions, component locations, network/wiring relationships, calibration references, and cross-references without assuming that the booklet gives universal procedures.

Responsible activity	Boundary
Locate a named subsystem and its related reference sections	Use the official current booklet; do not republish its pages
Trace a generic information path across referenced sheets	Describe the navigation method in original words; do not recreate protected diagrams
Compare composite assumptions with a real OEM procedure	Treat every production vehicle as independent and current-source controlled
Create original practice scenarios	Do not solicit, reconstruct, or share live or recalled exam questions
Cite public ASE task domains	Do not use ASE logos or imply endorsement of this handbook

Table 22.2. The booklet is a cited navigation source, not content to copy into this book.

A strong navigation exercise asks the reader to state which reference section would answer a question, what information is still missing, and why a real service decision would return to current OEM sources. That practice builds cross-reference discipline while keeping this independent Project DRIVE book original and respecting ASE ownership.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. A calibration routine completes despite an undocumented floor slope. What conclusion is justified?
2. Why should programming and calibration be listed separately on a work record?
3. How can the ASE composite booklet improve engineering skill without being copied?
4. A dynamic calibration does not complete. Which evidence classes should be reviewed before repeating it?

Answer notes

- Only that the controller accepted its monitored conditions. If floor geometry is a procedure prerequisite and was not established, the validity of setup evidence remains unresolved.
- They change different system states: executable/configuration content versus a physical/reference relationship. Separate records improve traceability and show whether each required operation occurred.
- Use it to practice locating descriptions, following cross-references, and separating given facts from missing information. Then apply the method-not its diagrams or wording-to original scenarios and real OEM research.
- Exact vehicle/procedure, environmental and road conditions, prerequisite DTCs/states, sensor visibility, speed/marking criteria, alignment/geometry, software/configuration, time/distance progress, and scan-tool instructions should be checked.

CHAPTER TAKEAWAY Calibration quality comes from controlled procedure evidence and appropriate verification. Reference-book navigation supports reasoning, but only current OEM information controls production-vehicle work.

CHAPTER 23 | VERIFICATION AND VALIDATION

Requirements, Scenarios, ODDs, Metrics, and the V-Model

Validation is not driving until nothing goes wrong; it is a traceable argument built from requirements, scenario coverage, measurements, and known limits.

Source anchors: R12, R16, R20, R23, R32, R38

LEARNING OBJECTIVES

- Distinguish verification from validation and trace requirements to evidence.
- Structure functional, logical, and concrete scenarios around an operational design domain.
- Choose metrics and pass criteria that expose performance, uncertainty, transitions, and regressions.
- Explain the roles and limits of MIL, SIL, HIL, VIL, proving-ground, and public-road evidence.

The V-model as a traceability discipline

System development decomposes stakeholder and vehicle needs into system, subsystem, component, software, hardware, and interface requirements. Integration builds the system back upward while tests provide evidence at corresponding levels. The V-model is useful when it preserves traceability and change impact, not when it becomes a rigid sequence that delays learning. Simulation and early prototypes can test assumptions before implementation is complete.

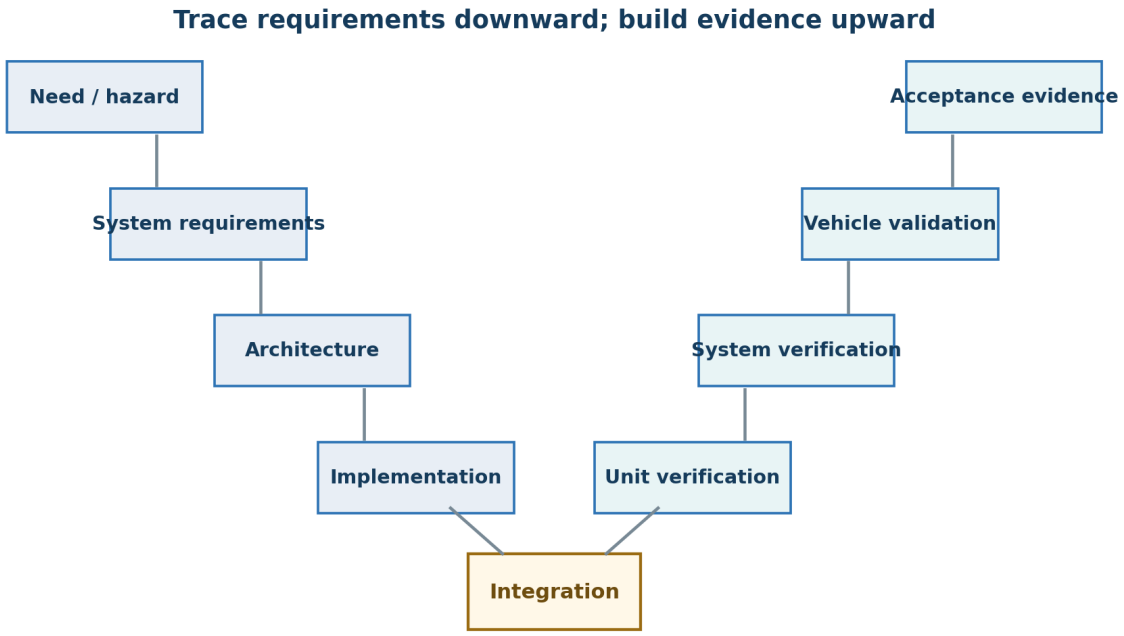


Figure 23.1. Original V-model view connecting requirement decomposition to integration evidence and vehicle validation.

Evidence level	Primary purpose	Representative question
Unit/component	Check a bounded implementation item	Does the estimator update correctly for controlled inputs and edge values?
Subsystem	Check interacting functions/interfaces	Does perception output meet timing and uncertainty requirements?
System	Check integrated vehicle behavior	Does the function respond correctly across required scenarios and degradation?
Validation	Check intended use and stakeholder need	Does behavior remain acceptable and understandable in the real operating context?

Table 23.1. Evidence meaning depends on the requirement level it addresses.

Scenario engineering

A functional scenario describes the situation in broad language: an ego vehicle follows a lead vehicle on a curved highway. A logical scenario defines parameter ranges and relationships: speeds, gaps, curvature, friction, visibility, lane widths, target behavior, and sensor conditions. A concrete scenario selects exact values and initial states for one reproducible test. This hierarchy turns an infinite world into reviewable coverage claims.

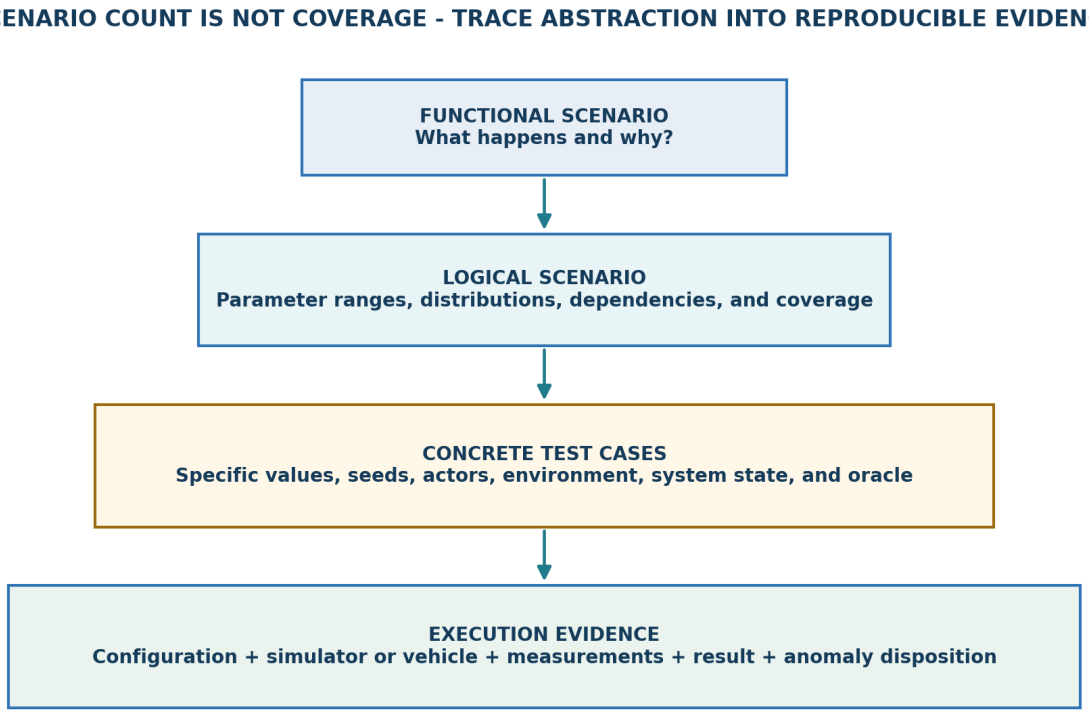


Figure 23.2. Original scenario pyramid from functional descriptions through logical parameter ranges to concrete test cases and replayable evidence.

- Road: geometry, markings, surface, grade, intersections, construction, and roadside structures.
- Environment: light, weather, visibility, temperature, contamination, and electromagnetic/acoustic context.
- Actors: type, size, pose, appearance/reflectivity, motion, intent, occlusion, and interaction.
- Ego: speed, path, load, tires, friction, sensor/software configuration, and fault state.
- Driver/user: engagement, command, override, response, misuse, attention, and interface state.
- Events: cut-in, crossing, stop, merge, object appearance, ODD exit, fault, or loss of communication.

COVERAGE STATEMENT A scenario catalog does not prove complete coverage. State which ODD dimensions, parameter interactions, rare events, and safety-critical boundaries are represented-and which remain open.

Metrics, oracles, and pass criteria

A test oracle determines expected behavior or a method for judging it. Exact expected values may come from requirements, analytical models, calibrated ground truth, a trusted reference implementation, or an approved human review policy. Each oracle has uncertainty. Ground-truth equipment must be

synchronized and calibrated; human labels require policy and agreement analysis; reference software can share the same defect as the test item.

Metric family	Examples	Caution
Perception	Precision/recall, range error, lane error, calibration	Aggregate scores can hide severe scenario partitions
Tracking	RMSE, ID switches, continuity, latency, covariance consistency	State accuracy can look good while identity is wrong
Control	Gap/path error, overshoot, jerk, response time, stability	Comfort and safety limits interact with road/actuator state
Safety/function	Collision avoidance/mitigation, false interventions, degradation	Event frequency alone may not represent severity or exposure
System quality	Availability, compute, network latency, thermal margin, diagnostics	Nominal performance may hide boundary collapse

Table 23.2. Metrics must connect to requirements and scenario partitions.

Pass criteria should be defined before observing the preferred result. A criterion includes the scenario range, measurement method, tolerance, timing window, allowed exceptions, confidence, and required artifacts. Statistical claims need sample-size and independence reasoning. A pass in ten nearly identical drives does not equal coverage of ten meaningful conditions.

Test environments and evidence ladders

Environment	Strength	Limit
MIL	Early algorithm/model exploration and parameter sweeps	Model fidelity and implementation effects are absent
SIL	Actual software logic, repeatability, automation, fault injection	Real hardware, timing, and physical sensor effects may be abstracted
HIL	Real controller with simulated plant/network/inputs	Sensor/environment and full-vehicle realism remain bounded
VIL	Vehicle/controller integrated with controlled virtual or injected scenario	Interface safety and realism require careful validation
Proving ground	Controlled physical actors, surfaces, and repeatability	Finite scenarios and instrumentation limitations
Public road	Natural complexity and long-tail discovery	Low repeatability, safety constraints, incomplete ground truth and exposure

Table 23.3. Evidence accumulates across environments; no single environment is sufficient.

1. Trace each test to a requirement, risk, scenario class, or regression concern.
2. Select the lowest-risk environment that can expose the target behavior with useful fidelity.
3. Validate the test setup, models, ground truth, timing, and fault-injection mechanism.
4. Capture configuration, inputs, outputs, logs, verdict, and anomaly notes reproducibly.
5. Promote evidence across environments while monitoring model-to-reality gaps.
6. Record limitations, unresolved failures, and the exact claim supported by the completed test set.

Coverage, simulation credibility, and data lineage

Scenario count is not coverage. Thousands of near-identical concrete cases can leave a critical boundary untouched. Coverage can be organized by ODD dimensions, actor maneuvers, geometry, timing, environmental conditions, system state, fault state, and safety-relevant parameter interactions. Combinatorial selection, search, optimization, field-data mining, expert analysis, and randomization can each find different gaps; none should be treated as a complete generator of safety evidence.

A simulator must be credible for the question being asked. Sensor appearance, vehicle dynamics, tire-road behavior, traffic actors, timing, and failure injection need only the fidelity required for the decision, but that adequacy must be argued and measured. Correlation against test data, sensitivity studies, uncertainty bounds, and known-invalid use cases are stronger than calling a model high fidelity. ASAM OpenDRIVE and OpenSCENARIO can improve exchange and repeatability; they do not validate model physics.

Every result should retain lineage: scenario definition, parameter values, random seed, map, actor models, vehicle configuration, software/model versions, calibration, simulator version, execution platform, measurement setup, oracle, and anomaly disposition. Without lineage, a passing result cannot be reproduced and a field failure cannot be compared fairly with development evidence.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. A feature passes 1,000 simulated cases. What is still needed before claiming vehicle validation?
2. Why should pass criteria be finalized before reviewing test results?
3. Convert 'pedestrian crosses ahead' into three logical-scenario parameters and one concrete case.
4. A public-road fleet records no collisions. Why is that insufficient evidence of safe behavior?

Answer notes

- Model validity, scenario relevance/coverage, actual software/hardware timing, sensors, actuators, vehicle dynamics, human interaction, physical tests, faults, boundaries, and traceability to intended use remain.
- Post-hoc criteria invite bias and allow a favored result to define success. Predefined criteria preserve auditability, though justified changes can be versioned and re-tested.
- Parameters could include ego speed, pedestrian entry time/speed, visibility/occlusion, friction, lateral starting point, or braking capability. A concrete case assigns exact controlled values and expected evidence.
- Exposure may be too small, scenarios may be unrepresentative, near misses and unsafe interventions may be hidden, reporting may be incomplete, and absence of observed harm does not demonstrate risk controls or boundary behavior.

CHAPTER TAKEAWAY A credible validation claim states the requirement, scenario space, test environment, oracle, metrics, configuration, evidence, and remaining limits. Volume of miles or cases cannot replace traceability.

CHAPTER 24 | SAFETY AND HIGHER AUTOMATION

Functional Safety, SOTIF, Cybersecurity, and the Path to ADS

Safety assurance requires three connected lenses: malfunction, functional insufficiency and foreseeable misuse, and security threats that can alter trusted behavior.

Source anchors: R5, R6, R7, R8, R15, R21, R22, R24, R35, R36, R39, R40, R43

LEARNING OBJECTIVES

- Distinguish functional-safety, SOTIF, and cybersecurity problem statements.
- Explain hazard analysis, safety goals, safety mechanisms, freedom from interference, and safety cases at a conceptual level.
- Connect ODD, perception limitations, fallback, redundancy, and minimum-risk behavior to higher automation.
- Build a responsible learning path from Project DRIVE theory into tool-based projects and engineering roles.

Three safety lenses

A vehicle may fail to brake because a controller malfunctioned, because every component worked as designed but perception could not interpret an unusual scene, or because an attacker manipulated trusted data. Functional safety addresses unreasonable risk caused by malfunctioning behavior of electrical/electronic systems. SOTIF addresses unreasonable risk from insufficiencies of intended functionality and foreseeable misuse in the absence of a traditional malfunction. Cybersecurity addresses threats to system assets and behavior. The analyses interact but should not be collapsed into one checklist.

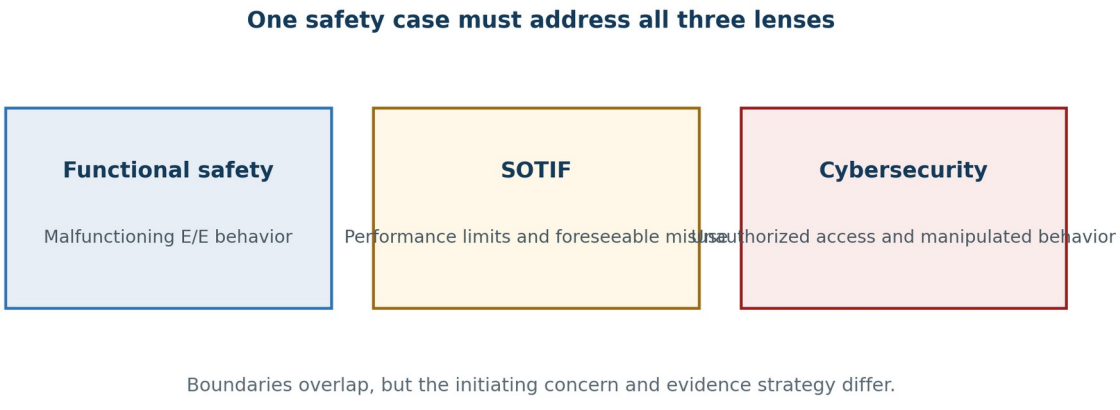


Figure 24.1. Original three-lens model: functional safety, SOTIF, and cybersecurity overlap at vehicle-level risk.

Lens	Example cause	Representative assurance activity
Functional safety	Corrupted sensor signal, stuck actuator command, compute fault	Hazard analysis, safety goals, diagnostics, redundancy, fault injection
SOTIF	Valid but insufficient perception in glare or unusual scene	Triggering-condition search, scenario expansion, limitation mitigation
Cybersecurity	Spoofed message, unauthorized update, compromised diagnostic access	Threat analysis, secure architecture, access control, monitoring, response

Table 24.1. One vehicle-level hazard may require evidence from all three disciplines.

Functional-safety reasoning

A functional-safety lifecycle begins by identifying item boundaries, hazardous events, operating situations, and safety goals. Risk classification informs development rigor; technical and hardware/software safety requirements allocate mechanisms such as monitoring, plausibility, watchdogs, redundancy, safe-state behavior, and diagnostic coverage. Verification confirms the implementation, while confirmation measures and safety management support independence and confidence appropriate to the work product.

- Item definition: function, boundaries, interfaces, assumptions, and operating modes.
- Hazardous event: hazard combined with an operational situation and affected road users.
- Safety goal: top-level requirement intended to prevent or mitigate unreasonable risk.
- Safe state or emergency operation: system condition or controlled behavior under fault.
- Safety mechanism: detection, control, redundancy, limitation, or transition that supports a safety requirement.
- Freedom from interference: evidence that one element cannot improperly affect another through shared resources.

The complete ISO 26262 standard defines formal processes and terms beyond this chapter and must be consulted by qualified practitioners. Project DRIVE's purpose is to build the mental link between a function map, a fault, the possible vehicle behavior, the hazardous situation, the safety requirement, and the evidence that the requirement is satisfied.

SOTIF, triggering conditions, and cybersecurity

SOTIF work asks where correct-by-design components and algorithms remain insufficient. Known unsafe scenarios can be mitigated through design change, ODD restriction, monitoring, driver communication, or performance improvement. Unknown unsafe scenarios require systematic exploration: simulation, field data, adversarial scenario generation, expert analysis, boundary search, and analysis of near misses. The aim is not to claim zero unknowns but to build evidence that residual risk is acceptably controlled under the applicable process.

Cybersecurity begins with assets and trust boundaries: sensor data, diagnostic services, update paths, keys, logs, control commands, maps, models, and personal information. Threat analysis considers feasible attack paths and impact. Secure boot, authenticated updates, access control, segmentation, intrusion monitoring, least privilege, logging, vulnerability response, and safe degradation can support the design. Security measures themselves must be assessed for timing, availability, serviceability, and safety interaction.

RESPONSIBLE BOUNDARY Project DRIVE studies defensive architecture and authorized testing. It does not encourage bypassing vehicle access controls, probing systems without permission, or conducting unsafe experiments on public roads.

From ADAS knowledge to higher automation

Higher automation extends the same engineering chain while changing responsibility and assurance. An ADS must sense and localize within its ODD, understand actors and free space, predict plausible futures, plan behavior and motion, control the vehicle, detect failures and ODD exits, interact with users and other road actors, and reach a fallback or minimum-risk condition appropriate to its level. Redundancy must address independent and common causes; operational monitoring must know when the assumptions supporting automation no longer hold.

ADS pipeline area	Project DRIVE theory base	Portfolio evidence
Sensors and state	Ch. 3, 6-13	Calibrated dataset with frames, timing, limits, and ego state
Perception/tracking	Ch. 10-16	Detection/tracking study with negative cases and uncertainty
Fusion/prediction	Ch. 17	Conflict-aware fusion notebook and trajectory-risk analysis
Planning/control	Ch. 18-21	Scenario-based ACC/AEB or lane-control simulation
Validation/safety	Ch. 22-24	Traceable test specification, fault campaign, and mini safety argument

Table 24.2. The 180-day course converts theory into reviewable engineering evidence.

1. Use Linux, Git, and Python to create reproducible data and analysis workflows.
2. Use ROS 2 and open architectures to learn interfaces, timing, modularity, and data lineage-not to claim production readiness.
3. Use OpenCV and public datasets to investigate image formation, perception metrics, and domain shift.
4. Use simulation such as CARLA and mathematical tools to generate controlled scenarios and test models safely.
5. Use CAN/Ethernet analysis tools on authorized data to connect software results to vehicle interfaces.
6. Build a capstone that states requirements, assumptions, versions, negative cases, metrics, safety limits, and next validation steps.

The engineering safety case

A safety case is a structured argument supported by evidence that a system is acceptably safe for a defined application and context. It is not a binder assembled after testing. Claims are decomposed into subclaims, strategies, assumptions, context, and evidence. Contradictory evidence and unresolved limits remain visible. The argument changes when software, hardware, maps, ODD, requirements, or operational experience changes.

1. State the top claim with system version, ODD, user role, and acceptance context.
2. Decompose by hazards, architecture, behavior, lifecycle, operations, and change management.
3. Link each subclaim to requirements, analyses, reviews, tests, field evidence, and competence records.
4. Identify assumptions, evidence limitations, independence, and configuration coverage.
5. Record defeaters: facts that could undermine the claim and how they are monitored or resolved.
6. Maintain the argument as a living artifact through updates and operational feedback.

AI assurance, field monitoring, and controlled evolution

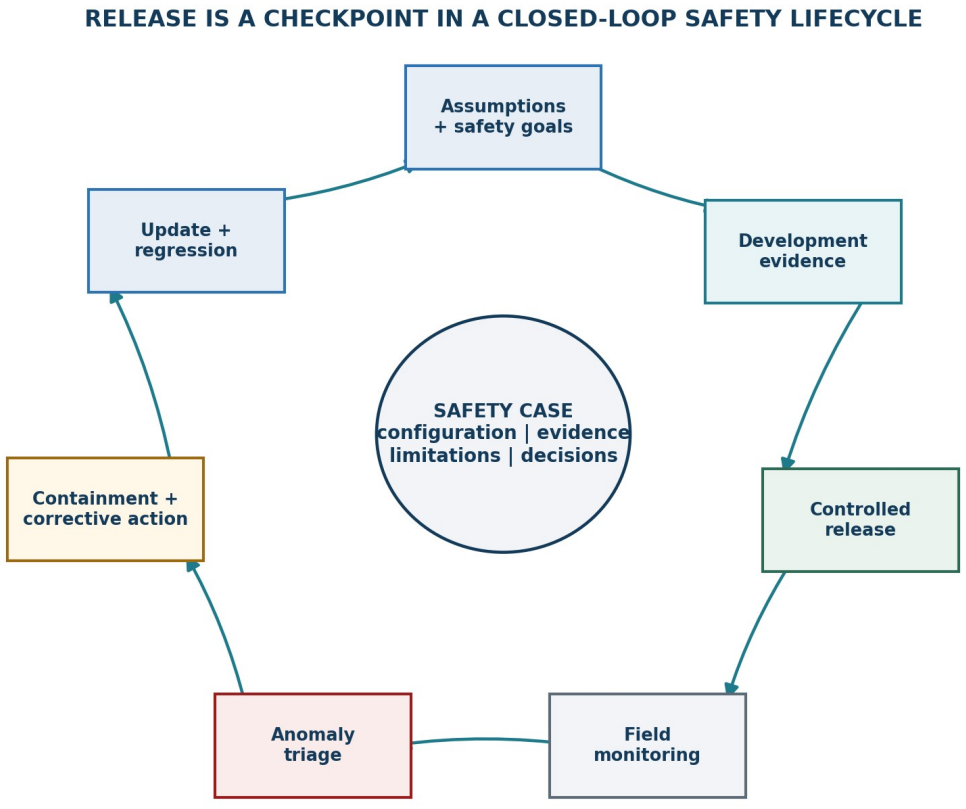


Figure 24.2. Original closed-loop safety lifecycle from design assumptions and release evidence through field monitoring, anomaly triage, corrective action, update, and regression.

AI-enabled behavior adds data and model dependencies to the safety case. ISO/PAS 8800 describes an automotive framework for safety-related AI properties, while NIST's voluntary AI Risk Management Framework provides broader governance and measurement concepts. These sources complement rather than replace ISO 26262 and SOTIF reasoning. The product argument must still show how data coverage, model limitations, integration, monitors, fallback, and lifecycle control address unreasonable risk.

Release is not the end of validation. Field monitoring can reveal new environmental patterns, sensor aging, software interactions, misuse, cybersecurity events, near misses, and rare failures. Monitoring must have defined signals, privacy and retention controls, triage criteria, escalation paths, and a way to distinguish product evidence from anecdote. Absence of recorded events is weak evidence when detection and exposure are unknown.

1. Preserve the released safety assumptions, configuration manifest, known limitations, and acceptance evidence.
2. Monitor leading and lagging indicators with known coverage and privacy boundaries.
3. Triage anomalies by severity, reproducibility, exposure, common cause, and uncertainty.
4. Contain risk through communication, operational restriction, service action, rollback, or update as authorized.
5. Verify the corrective change and run regression across linked software, data, model, calibration, hardware, and scenario partitions.
6. Update the safety case and field monitors so the organization learns rather than merely closes a ticket.

Engineering Judgment Check

Answer in complete reasoning chains: observation -> interpretation -> evidence gap -> next authorized action.

1. A perception algorithm misses an unusual object even though no component malfunctioned. Which safety lens leads, and which others may still contribute?
2. Why does hardware redundancy not automatically create a safe ADS fallback?
3. How can a cybersecurity control create a functional-safety concern?
4. What distinguishes a Project DRIVE portfolio project from a demonstration video?

Answer notes

- SOTIF leads because intended functionality is insufficient in the scenario. Functional-safety mechanisms may detect low confidence or provide degradation, while cybersecurity analysis ensures the input was not manipulated.
- Channels may share power, compute, software, calibration, environment, or design assumptions; arbitration and transition can fail; actuators and ODD may not support a minimum-risk maneuver. Independence and vehicle-level behavior need evidence.
- Authentication, timeout, segmentation, or security monitoring can add latency, deny an urgent message, block service, or consume resources. Safety and security requirements must be co-engineered.
- The portfolio artifact includes requirements, architecture, data/configuration provenance, assumptions, frames/time, negative and boundary cases, metrics, traceable results, limitations, safety boundaries, and reproducible work-not only a successful run.

CHAPTER TAKEAWAY Project DRIVE ends where professional engineering begins: with explicit responsibility, traceable evidence, controlled uncertainty, and humility about the conditions not yet demonstrated. Safety is an argument maintained across design, validation, operation, and change.

Appendix A - Project DRIVE 180-Day Course Map

The handbook provides the theory spine for the six Project DRIVE phases. The day ranges below are a learning map, not a claim that reading alone creates job qualification. Each phase should combine study, supervised practice where relevant, data review, tool work, and documented evidence.

Phase	Days	Reading	Course emphasis	Evidence
1	Days 1-30	Ch. 1-5	Vehicle architecture, ECUs, power, networks, diagnostics, sensor overview	System maps and fault-reasoning boards
2	Days 31-60	All chapters as needed	Linux, Python, Git, data handling, plotting, communication-tool foundations	Reproducible notebooks and traceable datasets
3	Days 61-90	Ch. 6-13, 18, 20, 22	ADAS functions, sensing, perception, vehicle state, calibration, and shared control	Function maps and verification plans
4	Days 91-120	Ch. 6, 10-15	OpenCV, image formation, ML foundations, detection, occupancy, transforms, and tracking	Camera/perception and scene-model studies
5	Days 121-150	Ch. 7, 12-17	Radar-camera fusion, localization, association, tracking, motion models, and filtering	Fusion and object-tracking evidence
6	Days 151-180	Ch. 18-24	Functions-to-control pipeline, planning, real-time software, ODD, validation, and safety	Integrated capstone and safety argument

Project DRIVE lesson rhythm

- Start with an accessible explanation, then restate the same idea in engineering language.
- Connect the concept to a real vehicle function and a realistic service or validation case.
- Build or update a virtual-vehicle system map showing signals, modules, frames, assumptions, and evidence gaps.
- Finish with an interview-style explanation and one artifact that can be reviewed by another engineer.
- Use weekly reviews and phase challenges to integrate topics instead of studying them as isolated facts.

Portfolio evidence standard

- State the problem and intended use without exaggerating outcomes.
- Identify assumptions, data sources, units, coordinate frames, and configuration versions.
- Trace each conclusion to observed evidence or a labeled engineering inference.
- Show negative and boundary cases, not only the example that succeeds.
- Describe limitations and the next validation step.

Appendix B - Practical Learning Labs

Lab 1: Vehicle function map

Choose one function such as AEB. Map sensors, inputs, networks, controller, actuators, driver interface, enable criteria, and post-event evidence. Do not assign universal thresholds.

Lab 2: Diagnostic evidence ladder

Given a warning message and one communication DTC, write an observation-only summary, three competing hypotheses, and the evidence required to separate them.

Lab 3: CAN reasoning board

Draw a generic two-bus gateway topology. Analyze how an open, short, lost power supply, or failed terminating path might change communication and resistance observations.

Lab 4: Camera limitation catalog

Collect public, non-proprietary examples of glare, low contrast, rain, obstruction, lane-marking loss, and mounting shift. Separate normal limitation from service fault.

Lab 5: Radar geometry

Sketch range, azimuth, relative velocity, and object angle. Explain why a mechanically secure bracket can still be misaligned relative to the vehicle thrust line.

Lab 6: Calibration readiness packet

Build a blank, product-neutral checklist for procedure source, vehicle state, alignment evidence, target/tool identification, bay conditions, scan records, and final verification.

Lab 7: Tracking notebook

Simulate a constant-velocity object with noisy measurements. Plot truth, measurements, estimate, and uncertainty. Explain one missed detection and one false association.

Lab 8: Fusion conflict review

Create a case where camera classification and radar kinematics disagree. Define checks for time, geometry, confidence, track history, and environmental context before selecting an action.

Lab 9: Scenario catalog

Write one functional scenario, three logical variations, and five concrete tests for lane support or AEB. Include pass criteria and evidence capture.

Lab 10: Mini safety argument

For one function, separate malfunctioning behavior, intended-functionality insufficiency, foreseeable misuse, and cybersecurity concerns. Link each to a verification activity.

Lab 11: Dataset and model evidence audit

Create a product-neutral dataset card for one perception task. Define partitions, leakage controls, label policy, scenario coverage, metrics, known gaps, model/runtime identity, and field-monitoring questions.

Lab 12: Occupancy and unknown-space study

Draw a top-down grid for a parked-vehicle occlusion. Mark observed free, occupied, and unknown cells, then compare two candidate paths and explain the risk policy near hidden emergence zones.

Lab 13: Planning decision log

For a merge or blocked-lane scenario, list behavior alternatives, hard constraints, costs, predicted actor modes, rejected trajectories, fallback, and the evidence needed to reproduce the decision.

Lab 14: End-to-end timing budget

Assign acquisition, network, compute, fusion, planning, control, and actuator budgets to a generic function. Analyze queue growth, one deadline miss, thermal slowdown, stale-data handling, and monitoring.

Appendix C - Glossary

Term	Working definition
ADAS	Advanced driver assistance systems; driver-support functions commonly associated with SAE Levels 0-2.
ADS	Automated driving system; the hardware and software capable of performing the entire dynamic driving task within its designed scope.
AEB	Automatic emergency braking; a collision-intervention function that may apply braking when a forward collision is judged imminent.
ASIL	Automotive Safety Integrity Level used within ISO 26262 risk classification and development rigor.
Association	The process of matching a new sensor detection to an existing object track or deciding that it begins a new track.
Backpressure	A condition in which a producer creates data faster than a consumer or communication path can process it, requiring a policy to block, drop, decimate, queue, or degrade.
BEV	Bird's-eye-view representation that places scene information in a top-down coordinate system for spatial fusion or planning.
Bias	A systematic sensor error that shifts measurements away from the true value.
BSW	Blind spot warning.
Calibration	A controlled process that establishes or corrects the relationship between a sensor/system and its required reference according to a specified procedure.
CAN	Controller Area Network, a message-oriented vehicle communication protocol.
CAN FD	CAN with Flexible Data-rate, supporting a larger payload and a faster data phase than Classical CAN.
CNN	Convolutional neural network, a learned model architecture that uses shared local filters and is widely applied to grid-like data such as images.
Confidence	A quantified or categorical expression of how strongly available evidence supports an estimate; it is not a guarantee.
Covariance	A matrix describing estimation uncertainty and correlation among state variables.
Deadline	The latest time by which a task or end-to-end computation must finish for its result to remain acceptable.
Distribution shift	A difference between development and deployment data distributions that can reduce model validity or performance.
DLC	Data link connector used for authorized diagnostic access.
DMS	Driver monitoring system.
Domain controller	A controller that consolidates several related vehicle functions or ECUs within an architectural domain.
DTC	Diagnostic trouble code; evidence that a monitored condition met defined fault criteria, not a complete root-cause diagnosis.
Dynamic calibration	A manufacturer-specified calibration performed while the vehicle is driven under defined conditions.
Dynamic driving task	The real-time operational and tactical functions required to operate a vehicle in on-road traffic, as defined in driving-automation taxonomy.
ECU	Electronic control unit.
Ego vehicle	The vehicle whose sensors, state, and decisions are being analyzed.
Extrinsic calibration	The rotation and translation relating one sensor coordinate frame to another reference frame.
False negative	A relevant object or condition that exists but is not detected or classified as such.
False positive	A reported object or condition that does not correspond to the relevant reality.
FCW	Forward collision warning.
Field of view	The angular region observable by a sensor.
Freeze frame	A stored snapshot of selected data associated with a fault event.
Fusion	The combination of information from multiple measurements or sources to produce a more useful estimate.
Gateway	A module that routes, filters, translates, or protects communication among vehicle networks.

Term	Working definition
GNSS	Global navigation satellite system.
Ground truth	A trusted reference measurement or annotation used to evaluate an estimate or system output.
HIL	Hardware-in-the-loop testing.
Homogeneous transform	A matrix representation combining rotation and translation between coordinate frames.
IMU	Inertial measurement unit, typically containing accelerometers and gyroscopes.
Inference	Execution of a trained model on new input to produce an output such as a class, geometry, mask, state, or trajectory.
Initialization	A procedure that establishes a module or algorithm's starting state or learned reference values.
Intrinsic calibration	Parameters internal to a sensor model, such as camera focal length and optical distortion.
IoU	Intersection over Union, a common overlap metric for detection or segmentation.
Jitter	Variation in latency, execution time, sample period, or message arrival timing.
Kalman filter	A recursive estimator that combines a process model and noisy measurements while propagating uncertainty.
Latency	Elapsed time between an originating event or measurement and the point at which a usable response becomes available.
Lateral control	Control of vehicle heading and lateral path, usually through steering.
LiDAR	Light detection and ranging, generally producing range measurements or 3D point clouds.
Localization	Estimation of the ego vehicle's pose relative to a map or reference frame.
Longitudinal control	Control of vehicle speed, acceleration, and braking along the path of travel.
Measurement model	A mathematical relation between system state and expected sensor observation.
Minimum risk condition	A stable, stopped, or otherwise reduced-risk state reached when an automated system cannot continue as designed.
Model drift	Degradation or change in model behavior as data, environment, hardware, or operating conditions differ from development assumptions.
Model predictive control	A receding-horizon method that repeatedly optimizes a future trajectory or control sequence, applies an initial portion, and solves again from updated state.
Object track	A time-linked estimate of an object's identity, state, and uncertainty.
Occupancy grid	A spatial lattice whose cells store evidence or probability for occupied, free, and often unknown space.
ODD	Operational design domain; operating conditions in which a driving automation system is designed to function.
OEM	Original equipment manufacturer.
Operational limitation	A condition outside or near the boundary of expected performance that is not necessarily a component malfunction.
Out-of-distribution	Input or conditions that differ meaningfully from the data distribution used to develop or validate a model.
Path	A geometric curve or sequence of poses without necessarily specifying the time at which each point is reached.
Perception	The process of interpreting sensor data to estimate relevant features, objects, lanes, free space, or conditions.
Pose	Position and orientation relative to a defined coordinate frame.
Post-scan	A diagnostic scan performed after repair or procedure completion to support verification and documentation.
Pre-scan	A diagnostic scan performed before work to document system state and identify relevant conditions.
Process noise	Uncertainty representing unmodeled dynamics or disturbance in a state-transition model.
Quality of service	Communication policies governing properties such as reliability, history, durability, deadlines, queue depth, and liveliness.
Radar cross section	A measure related to how strongly an object reflects radar energy; it depends on geometry, material, angle, and frequency.

Term	Working definition
Real-time system	A system whose correctness depends on producing acceptable results within defined timing bounds, not merely on average computational speed.
Regression test	A repeated test used to determine whether a change affected previously verified behavior.
Residual	The difference between a measurement and its predicted value.
Risk	A combination of the severity and likelihood/exposure of harm, interpreted within the applicable safety process.
Rolling shutter	An image-capture method in which sensor rows are exposed at different times, potentially distorting rapidly moving scenes.
Scenario	A structured description of actors, environment, roadway, maneuvers, and events used for analysis or testing.
Scene graph	A structured representation of actors, elements, and relationships in a scene.
Sensor fusion	A fusion process specifically combining sensor-derived information.
Shortcut learning	A model's reliance on an easy correlation or artifact that predicts development labels but does not represent the intended concept robustly.
SIL	Software-in-the-loop testing.
SOTIF	Safety of the Intended Functionality; addressing unreasonable risk from functional insufficiencies and foreseeable misuse.
Static calibration	A manufacturer-specified calibration performed with the stationary vehicle and controlled setup.
Target	A specified visual or reflective reference used by a calibration or test procedure.
Time synchronization	Alignment of measurements to a common time basis or compensation for known latency.
Trajectory	A time-parameterized path or state sequence that includes timing and therefore speed, acceleration, and interaction timing.
Transformer	A learned model architecture that uses attention mechanisms to relate information across positions, views, objects, or time.
TTC	Time to collision under stated motion assumptions.
UDS	Unified Diagnostic Services, standardized diagnostic-service concepts commonly used in road vehicles.
Uncertainty	What is not known exactly about a measurement, estimate, model, or condition.
V2X	Vehicle-to-everything communication among vehicles, infrastructure, and other road users or devices.
Validation	Evidence that the intended use and stakeholder needs are satisfied in the relevant context.
Verification	Evidence that specified requirements or design outputs are satisfied.
VIL	Vehicle-in-the-loop testing.
Voxel	A volumetric grid cell used to discretize three-dimensional space or point-cloud data.
Watchdog	A monitor that checks progress or timing and initiates a defined response when expected activity is missing.
Yaw rate	Rate of rotation about the vehicle's vertical axis.
Zonal controller	A controller that aggregates sensors, actuators, and input/output by physical region of a vehicle and connects them to higher-level compute.

Appendix D - Complete Theory Competency Map

Use this map as a self-assessment, not as a claim of job qualification. For each domain, progress from recognition to explanation, then to evidence-based analysis and a reviewable artifact. A learner who cannot state assumptions, frames, timing, uncertainty, and source boundaries has not yet mastered the topic.

Domain	Chapters	Working mastery	Evidence artifact
Systems and responsibility	1-2	Map function boundaries, DDT responsibility, ODD, fallback, and evidence gaps	Function/system map with assumptions
Vehicle motion and E/E	3-5	Work with frames, dynamics, power, networks, diagnostics, gateways, and architecture	Signal and dependency map
Sensors	6-9	Explain measurement physics, geometry, timing, installation, limitations, and plausibility	Sensor limitation matrix
Machine learning and perception	10-11	Explain data splits, leakage, model lifecycle, metrics, confidence, and scene outputs	Dataset/model evidence audit
Localization and scene models	12-13	Reason about maps, calibration, time, occupancy, BEV, occlusion, and unknown space	Spatial consistency study
Tracking and estimation	14-17	Apply gating, lifecycle, motion models, covariance, filtering, fusion, and prediction	Tracking/fusion notebook or report
ADAS functions	18	Trace sensing-to-actuation dependencies, enable criteria, state machines, and limitations	Feature dependency map
Planning and control	19-20	Separate behavior, path, trajectory, constraints, optimization, arbitration, and driver role	Scenario decision log
Software and compute	21	Build timing, interface, resource, health, version, update, and V2X trust arguments	End-to-end timing budget
Calibration and service evidence	22	Research triggers, verify readiness, execute authorized procedures, and document evidence	Product-neutral readiness packet
Validation	23	Trace requirements through scenarios, metrics, oracles, coverage, simulation, and vehicle evidence	Test specification and result report
Safety assurance	24	Integrate functional safety, SOTIF, cybersecurity, AI assurance, misuse, field monitoring, and change	Mini safety case

Five mastery levels

Level	Evidence of learning
1 - Recognize	Define the term and identify it in a system map without exaggerating understanding.
2 - Explain	Teach the concept in plain language and engineering language, including one limitation.
3 - Analyze	Trace inputs, outputs, frames, timing, uncertainty, dependencies, and competing hypotheses.
4 - Verify	Design a safe, repeatable test with requirements, scenarios, metrics, configuration, and evidence.
5 - Integrate	Connect the topic to vehicle behavior, safety argument, lifecycle change, and downstream consequence.

COMPLETION TEST You are ready to move beyond theory when you can explain the complete chain, identify what remains unknown, select authoritative sources, design evidence without unsafe experimentation, and accept review from someone who can challenge your assumptions.

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Responsible use of the ASE Composite Vehicle booklet

The official Composite Vehicle Type 1 Reference Document is a copyrighted ASE publication made available for L4 preparation and testing reference. This handbook cites it and teaches navigation strategies but does not reproduce its wiring diagrams, component illustrations, calibration charts, or official question content. Readers should download the current copy directly from the ASE L4 page.

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ENGINEERING JUDGMENT BEFORE ASSUMPTION

Research the procedure. Define the frame. Preserve uncertainty.
Verify the evidence. Document the boundary.

PROJECT DRIVE | INDEPENDENT ADAS SYSTEMS-ENGINEERING LEARNING