



SURFACE VEHICLE INFORMATION REPORT

J3295™

OCT2025

Issued

2025-10

Cooperative Perception Concept of Operations

RATIONALE

Cooperative perception (CP) has been a subject of interest for V2X communities in North America, Europe, and Asia. CP services will enable transportation users to maintain an enhanced real-time spatial representation of objects in the area nearby through exchanging sensor data. The focus of this report is on the user needs associated with applications that rely on CP information. It is expected to be used as a reference for system designers and message developers.

TABLE OF CONTENTS

1.	SCOPE	5
2.	REFERENCES	5
2.1	Applicable Documents	5
2.1.1	SAE Publications	5
2.1.2	ISO Publications	5
2.1.3	Other Publications	5
3.	DEFINITIONS	7
4.	ABBREVIATIONS	9
5.	CONCEPT OF OPERATIONS	10
5.1	Current Situation and Problem Statement	10
5.1.1	Data Fusion	10
5.1.2	Communication Bandwidth and Latency	10
5.1.3	Computational Architecture	10
5.1.4	Object Sensing and Positioning Accuracy	10
5.1.5	Latency	11
5.2	Local Detection	12
5.2.1	RSU Detection	12
5.2.2	RV Detection	12
5.3	CP Data Flow Case Descriptions	13
5.3.1	Data Flow Case 1: RSU Detection and CP Data Sharing with HV	13
5.3.2	Data Flow Case 2: RV Detection and CP Data Sharing with HV	14
5.3.3	Data Flow Case 3: RV Detection and CP Data Sharing with RSU	14
5.3.4	Composite Cases	15
5.4	Motion Model Considerations	15
5.5	Coordinate System Considerations	16
5.6	Summary	17

SAE Executive Standards Committee Rules provide that: "This report is published by SAE to advance the state of technical and engineering sciences. The use of this report is entirely voluntary, and its applicability and suitability for any particular use, including any patent infringement arising therefrom, is the sole responsibility of the user."

SAE reviews each technical report at least every five years at which time it may be revised, reaffirmed, stabilized, or cancelled. SAE invites your written comments and suggestions.

Copyright © 2025 SAE International

All rights reserved. No part of this publication may be reproduced, stored in a retrieval system, transmitted, in any form or by any means, electronic, mechanical, photocopying, recording, or otherwise, or used for text and data mining, AI training, or similar technologies, without the prior written permission of SAE.

TO PLACE A DOCUMENT ORDER:
Tel: 877-606-7323 (inside USA and Canada)
Tel: +1 724-776-4970 (outside USA)
Fax: 724-776-0790
Email: CustomerService@sae.org
http://www.sae.org

SAE WEB ADDRESS:

Full document details: SAE J3295_202510

For more information on this standard, visit https://www.sae.org/standards/content/J3295_202510/

Documents



Standard, visit Sharing Hub

6.	REFERENCE ARCHITECTURE.....	18
6.1	Architecture Elements.....	19
6.1.1	Equipped Vehicles (HV and RV).....	19
6.1.2	Roadside Infrastructure Unit (RSU).....	19
6.1.3	V2X Communication Network.....	19
6.1.4	MEC/Cloud.....	19
6.1.5	Object (Unequipped Vehicle, Unequipped VRU, Obstacle).....	19
6.1.6	Vehicle and Infrastructure Sensors.....	19
6.1.7	Positioning.....	20
6.2	Architectural Needs and Preconditions.....	20
7.	FEATURES.....	21
7.1	Data Fusion and Perception Level.....	21
7.1.1	Early/Sensor Data Fusion.....	22
7.1.2	Mid/Deep/Feature Level Data Fusion.....	22
7.1.3	Object Level/Late Data Fusion.....	22
7.2	Positioning Accuracy Needs.....	22
7.2.1	Vehicle Positioning and Error Estimation.....	23
7.2.2	Object Range and Angle Detection Errors.....	24
7.2.3	Vehicle (RV and HV) Heading and Error Estimation.....	26
7.2.4	Uncertainty Scaling Factors in 1D and 2D.....	28
7.2.5	Uncertainty and Positioning Error Approximations.....	29
7.3	Positioning Impact on Timing.....	31
7.3.1	Probabilistic Models of Timing.....	31
7.4	Latency Impacts and Needs.....	33
7.4.1	V2X End-to-End Application.....	33
7.4.2	V2X End-to-End Latency.....	36
7.4.3	Cooperative End-to-End Latency.....	37
7.4.4	Common Time Reference.....	39
7.4.5	CP Message Size and Object Age.....	40
7.5	Intersection over Union in Accuracy Analysis.....	41
7.5.1	IoU Description.....	41
7.5.2	Probability @ IoU as an Evaluation Metric.....	42
7.6	Object Perception Quality (OPQ).....	44
7.7	Performance Needs Assessment Process.....	46
8.	APPLICATION OF UNCERTAINTY ANALYSIS TO ILLUSTRATIVE SCENARIOS.....	48
8.1	Local Detection: RSU versus RV.....	48
8.2	Combined Positioning and Sensing Errors.....	50
8.3	Occluded VRU Avoidance.....	53
8.4	Cooperative Permissive Left Turn Across Opposing Traffic with Infrastructure Guidance.....	55
8.5	Summary.....	58
9.	APPLICATION OF IOU METRIC ANALYSIS TO CASE EVALUATIONS.....	58
9.1	Local Detection: RSU versus RV.....	59
9.2	CP Data Flow Cases 1, 2, and 3.....	60
9.3	Summary.....	64
10.	EVALUATION OF SHARED DATA TYPES.....	65
10.1	Vehicle Positions and Error Estimates.....	66
10.2	Object Position Offsets and Error Estimates.....	67
10.3	Object Speed, Heading, and Error Estimates.....	67
10.4	Object Dimensions and Error Estimates.....	68
10.5	Time Stamps and Error Estimates.....	69
10.6	Object Perception Quality.....	69
10.7	Motion Model and Covariance Matrix.....	69

11.	CONCLUSIONS AND RECOMMENDATIONS.....	70
11.1	Individual Error Impact and Error Accumulation Effect	70
11.2	Global versus Local Coordination Systems	71
11.3	Performance Assessment Framework and Use Case Evaluations	71
11.4	Shared Data Types	72
12.	NOTES	73
12.1	Revision Indicator.....	73
APPENDIX A - Confidence and Uncertainty Translations		74
APPENDIX B - Derivation of Relative Position Error and Approximation		75
APPENDIX C - Object Ranging and Angular Errors in Vehicle Sensing Systems		78
APPENDIX D - Coordinate Transformations for Host and Remote Vehicles		80
APPENDIX E - Probability @ IoU for Different Uncertainty Shapes.....		82
Figure 1	Illustration of RSU detection	13
Figure 2	Illustration of RV detection	13
Figure 3	Data Flow Case 1: RSU detection and CP data sharing with HV	14
Figure 4	Data Flow Case 2: RV detection and CP data sharing with HV	14
Figure 5	Data Flow Case 3: RV detection and CP data sharing with RSU	15
Figure 6	Reference architecture for cooperative perception	18
Figure 7	Vehicle sensor types and their typical ranges and functions	21
Figure 8	Levels of perception and sensor data fusion	21
Figure 9	Uncertainty (error) ellipse in 2D positioning systems.....	23
Figure 10	Object detection and its measurement errors	25
Figure 11	A simplified view of the object angular error impact	26
Figure 12	A simplified view of RV heading error impact	27
Figure 13	A simplified view of HV heading error impact	27
Figure 14	Illustration of relative position error	30
Figure 15	Positioning uncertainty and timing variability	32
Figure 16	Confidence in reaching a limit line within a time T_{max}	33
Figure 17	Illustration of V2X end-to-end application	34
Figure 18	Illustration of latency and IPG	34
Figure 19	Relationship between latency, reliability, and packet error rate	35
Figure 20	Illustration of cooperative end-to-end latency	37
Figure 21	A simplified view of the cooperative E2E latency impact as a CP timing error.....	38
Figure 22	Illustration of txReferenceTime, measurementDeltaTime, and rxTimeStamp	39
Figure 23	Illustration of IoU computation	41
Figure 24	Object detection result examples: poor, good, and excellent	42
Figure 25	Estimated object positions as points versus bounding boxes.....	42
Figure 26	Illustration of true bounding box and reference coordinate system	43
Figure 27	Position error uncertainties 1.06 m, 1.50 m, and 2.45 m @ 95%	43
Figure 28	CDF curves of IoU values for position error uncertainties 1.06 m, 1.50 m, and 2.45 m @ 95%	43
Figure 29	Example dimensions of car and truck	45
Figure 30	CDF curves of IoU for object being a pedestrian, car, and truck for position error 1.06 m @ 95%	46
Figure 31	Performance needs assessment process.....	47
Figure 32	Local detection: RSU versus RV - error sources presented	48
Figure 33	Error accumulation illustrative scenario	51
Figure 34	Occluded VRU scenario (from SAE J3251_202308).....	53
Figure 35	Total braking distance parameters (from SAE J3251_202308).....	53
Figure 36	Permissive left-turn scenario (from SAE J3282_202406).....	55
Figure 37	Two distinct cases for POV1 and POV2 configurations (for SAE J3282).....	55
Figure 38	Simulation parameters for (a) RSU detection example and (b) RV detection example	59
Figure 39	CDF curves of IoU values for RSU detection example and RV detection example	60
Figure 40	CP Data Flow Case 1 - error sources presented	61
Figure 41	CP Data Flow Case 2 - error sources presented	61
Figure 42	CP Data Flow Case 3 - error sources presented	61
Figure 43	Simulation parameters for examples of CP Data Flow Cases 1 and 2.....	62
Figure 44	CDF curves of IoU values for examples of CP Data Flow Cases 1 and 2.....	62

Figure 45	Simulation parameters for examples of CP Data Flow Cases 3 and 2.....	63
Figure 46	CDF curves of IoU values for examples of CP Data Flow Cases 3 and 2.....	64
Figure 47	Result summary for simulation examples examined	65
Table 1	Summary of section references for key CP topics.....	17
Table 2	Key probability values for positioning error in the horizontal (X-Y) plane	24
Table 3	Object position offset errors given fixed angular errors	27
Table 4	Uncertainty scaling factors in 1D and 2D	29
Table 5	Typical examples of position error uncertainty in the horizontal plane	30
Table 6	V2X E2E latency and reliability values specified by 3GPP and 5GAA	36
Table 7	Probability @ IoU ≥ 0.5 for position error uncertainties 1.06 m, 1.50 m, and 2.45 m @ 95%	44
Table 8	Probability @ IoU ≥ 0.5 or ≥ 0.1 for different objects in terms of sizes.....	46
Table 9	Analytic results for local detection examples	50
Table 10	Analytic results for CP data flow case 2 - simplified example.....	52
Table 11	Analysis results for SAE J3251	54
Table 12	Analysis results for SAE J3251 when an RSU is in place of truck (V1).....	54
Table 13	Analysis results for SAE J3282 Case 1: POV1 unequipped.....	57
Table 14	Analysis Results for SAE J3282 Case 2: Both POV1 and POV2 Unequipped.....	57
Table 15	Key parameters evaluated for cooperative perception system.....	65
Table 16	Key parameters to be assembled in a sensor data message.....	66

1. SCOPE

This information report is a cooperative perception (CP) services concept of operations. Included is a description of CP systems and a description of the data potentially shared between its participants. The participants are the actors within the CP system, such as vehicles, bicycles, pedestrians and infrastructure. The types of data that can be shared among the actors are presented, and the types of features and applications that can be satisfied based on the types and accuracy of information shared are classified into categories. This report supports a wide variety of potential CP use cases ranging from connected-vehicle enabled driver-assistance applications (e.g., for collision avoidance) to connected automation.

2. REFERENCES

2.1 Applicable Documents

The following publications form a part of this specification to the extent specified herein. Unless otherwise indicated, the latest issue of SAE publications shall apply.

2.1.1 SAE Publications

Available from SAE International, 400 Commonwealth Drive, Warrendale, PA 15096-0001, Tel: 877-606-7323 (U.S. and Canada only) or +1 724-776-4970 (Outside U.S. and Canada), www.sae.org.

SAE J2735	V2X Communications Message Set Dictionary
SAE J2945/1	On-Board System Requirements for V2V Safety Communications
SAE J3161/1	Onboard System Requirements for LTE-V2X, V2V Safety Communications
SAE J3224	V2X Sensor-Sharing for Cooperative and Automated Driving
SAE J3251	Cooperative Driving Automation (CDA) Feature: Perception Status Sharing for Occluded Pedestrian Collision Avoidance
SAE J3256	Cooperative Driving Automation (CDA) Feature - Infrastructure-Based Prescriptive Cooperative Merge
SAE J3282	Cooperative Infrastructure CDA Feature: Cooperative Permissive Left Turn Across Opposing Traffic with Infrastructure Guidance

2.1.2 ISO Publications

Copies of these documents are available online at www.iso.org/store.

ISO 26262	Road vehicles - Functional safety
-----------	-----------------------------------

2.1.3 Other Publications

3GPP TS 22.186	Enhancement of 3GPP support for V2X scenarios; Stage 1 (Release 16), V16.2.0, 2019
3GPP TR 22.886	Study on enhancement of 3GPP Support for 5G V2X Services (Release 16), V16.2.0, 2018
5GAA V2XHAP	System Architecture and Solution Development; High-Accuracy Positioning for C-V2X 5GAA Automotive Association Technical Report, 2021
5GAA-T-220019	Use Case Implementations for Sensor Data-Sharing, 5GAA Automotive Association Technical Report, 2023
5GCAR_D2.1_v1.0	5GCAR Scenarios, Use Cases, Requirements and KPIs, 5G Communication Automotive Research and Innovation, 2017

CAR2CAR-2089	Technical Report on CPM Object Quality, CAR 2 CAR Communication Consortium, December 2021
ETSI TR 103 562	Intelligent Transport Systems (ITS); Vehicular Communications; Basic Set of Applications; Analysis of the Collective Perception Service (CPS); Release 2
ETSI TS 103 324	Intelligent Transport System (ITS); Vehicular Communications; Basic Set of Applications; Specification of the Collective Perception Service (CPS); Release 2, June 2023

Aidouni, M. (2019). *Evaluating Object Detection Models: Guide to Performance Metrics*. Available at <https://manalelaidouni.github.io/Evaluating-Object-Detection-Models-Guide-to-PerformanceMetrics.html>

Bai, Z., Wu, G., Barth, M., et al. (2022). *A Survey and Framework of Cooperative Perception: From Heterogeneous Singleton to Hierarchical Cooperation*. Cornell University. Available at <https://arxiv.org/abs/2208.10590>.

Caillot, A., Ouerghi, S., Vasseur, P., et al. (2023). Survey on Cooperative Perception in an Automotive Context. *IEEE Transactions on Intelligent Transportation Systems*, 23(9), 14204-14223.

Do, C. (2008). More on Multivariate Gaussians. Stanford University. Available at https://cs229.stanford.edu/section/more_on_gaussians.pdf

Everingham, M., Gool, L., Williams, C., et al. (2010). The Pascal Visual Object Classes (VOC) Challenge. *International Journal of Computer Vision*, 88(2), 303-338.

Goh, C., et al. (2024). Unbiased and Consistent Electro-Optical Camera Angular Measurements with Cross-Correlated Errors and Their Fusion. *Journal of Advances in Information Fusion*.

Hu, S., Fang, Z., Deng, Y., et al. (2024). *Collaborative Perception for Connected and Autonomous Driving: Challenges, Possible Solutions and Opportunities*. Cornell University. Available at <https://arxiv.org/abs/2401.01544>.

Rauch, A., Klanner, F., and Dietmayer, K. (2011). *Analysis of V2X Communication Parameters for the Development of A Fusion Architecture for Cooperative Perception Systems*. [Conference paper]. IEEE Intelligent Vehicles Symposium (IV), 685-690.

Shan, M., Narula, K., et al. (2021). Demonstrations of Cooperative Perception: Safety and Robustness in Connected and Automated Vehicle Operations. *Sensors* 2021, 21(1), 200. Available at <https://doi.org/10.3390/s21010200>.

Stuart, A. and Ord, J.K. (1994). *Kendall's Advanced Theory of Statistics: Volume 1 - Distribution Theory*. Hodder Arnold.

Volk, G., Delooz, Q., Schiegg, F., et al. (2021). *Towards Realistic Evaluation of Collective Perception for Connected and Automated Driving*. [Conference paper]. IEEE International Intelligent Transportation Systems Conference (ITSC), 1049-1056.

Wang, T., Manivasagam, S., Liang, M., et al. (2020). *V2Vnet: Vehicle-to-vehicle communication for joint perception and prediction*. [Conference paper]. European Conference on Computer Vision, 605-621.

Yeong, D.J., et al. (2021). Sensor and Sensor Fusion Technology in Autonomous Vehicles: A Review. *Sensors* 2021, 21(6), 2140. Available at <https://doi.org/10.3390/s21062140>.

Yu, H., Yang, W., Ruan, H., et al. (2023). *V2X-Seq: A Large-Scale Sequential Dataset for Vehicle-Infrastructure Cooperative Perception and Forecasting*. [Conference paper]. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 5486-5495.

3. DEFINITIONS

3.1 BOUNDING BOX

A generally rectangular box that defines the outside boundary of a vehicle or object, including side protrusions, such as side mirrors.

3.2 CONFIDENCE

Confidence in the positioning context of this report is the probability level at which the positioning system determines the associated “uncertainty” (i.e., positioning error estimate) (see definition [3.14](#)). In other contexts, such as object detection, confidence can be associated with the probability of presence of an object (refer to ETSI TR 103 562).

3.3 COOPERATIVE PERCEPTION (CP)

An advanced Intelligent Transportation System (ITS) technology where equipped vehicles and roadside infrastructure units collaboratively sense their surroundings using sensors (such as cameras, radar, and lidar) and then exchange this fused perception information (e.g., positions, speeds, and classifications of road users and objects) through Vehicle-to-Everything (V2X) communication. This allows vehicles to better understand their environment, extending their perception range and improving road safety and traffic efficiency.

NOTE: Unlike Cooperative Awareness (CA), which focuses solely on equipped stations (such as vehicle or pedestrian) broadcasting their own state information (position, speed, heading), CP involves actively sharing and fusing detailed sensor-based environmental perception information, including non-connected or unequipped road users and occluded objects, thus significantly enhancing situational awareness.

3.4 EQUIPPED VEHICLE

Vehicle fitted with Advanced Driver Assistance Systems (ADAS) or Automated Driving Systems (ADS) that include onboard sensors and V2X communication capabilities, enabling the vehicle to actively share real-time perception data with other equipped vehicles and roadside infrastructure units.

NOTE: ISO 26262 governs functional safety levels that vehicle manufacturers will likely refer to when specifying V2X and ADAS fusion. Applying CP for throttle, brake, or steering control implies conformance to ISO 26262.

3.5 HOST VEHICLE (HV)

An equipped vehicle that receives transmissions from a roadside infrastructure unit or some remote vehicle (RV). An HV has its own sensing capabilities and can fuse the information received from RVs and roadside infrastructure units.

3.6 INTER-PACKET GAP (IPG)

The time gap between two consecutive received packets.

3.7 INTERSECTION OVER UNION (IoU)

A metric frequently used in object recognition and detection and is the ratio of the area of intersection of an estimated object's bounding box with its true (ground truth) bounding box divided by the union of these two bounding boxes.

3.8 LATENCY

It is the time taken to transmit an application message from the application layer of the source node to the application layer of the destination node. It is also referred to as “end-to-end delay.”

3.9 MOBILE EDGE COMPUTING (MEC)

A distributed computing capability that is optionally deployed in conjunction with infrastructure units or remotely in the cloud. The objective is to have powerful data fusion of sensed roadside conditions reported by vehicles and infrastructure elements.

3.10 OBJECT (O)

An object could be an inanimate obstacle (e.g., material that may have fallen from a truck), an unequipped vehicle, or a pedestrian.

3.11 PACKET ERROR RATE

The ratio of unsuccessfully received data packets to the total number of packets transmitted over a communication channel within a given period.

3.12 REMOTE VEHICLE (RV)

An equipped vehicle that senses its environment, optionally fuses such information with information it receives, and transmits its information to other vehicles, including a host vehicle, as well as to a roadside infrastructure unit.

3.13 ROADSIDE UNIT (RSU)

An infrastructure-based unit equipped with V2X communication and sensing and processing capabilities. It may also be optionally connected to cloud services or MEC platforms to support enhanced data processing and coordination.

NOTE: Sensors may be external to the RSU and mounted on surrounding infrastructure (e.g., poles, gantries, or buildings), or they may be integrated within the RSU enclosure itself. The configuration can vary depending on deployment needs, including environmental conditions, field of view requirements, and infrastructure constraints. In this report, RSU and roadside infrastructure unit are used interchangeably.

3.14 UNCERTAINTY (Unc)

Uncertainty is an estimate of the error accuracy, determined by the positioning system itself, based on its measurement of various input signal conditions and knowledge of its own design characteristics. Uncertainty is expressed in meters at a certain level of “confidence” or probability. It takes the shape of an ellipsoid in 3D and an ellipse (commonly referred to as “error ellipse”) in the horizontal plane (2D). An uncertainty of X meters at C% confidence means that the positioning system believes that the true location will fall within the X meters contour C% of the time. Uncertainty is not the actual positioning error, and using it directly as a measure of such error is an incorrect use of the metric and invalid.

3.15 UNEQUIPPED VEHICLE

A vehicle lacking ADAS/ADS or V2X communication capabilities and therefore cannot actively share its perception data. This vehicle is perceived by equipped vehicles and infrastructure sensors, and its information is shared among equipped participants for improved transportation safety and efficiency. An unequipped vehicle could be viewed as an “object.”

3.16 VULNERABLE ROAD USER (VRU)

A human road user who is not a vehicle occupant, such as a pedestrian, pedal cyclist, or wheelchair user. A VRU could be viewed as an “object.”

4. ABBREVIATIONS

ADS	Automated Driving System
ADAS	Advanced Driver Assistance Systems
BSM	Basic Safety Message
CA	Cooperative Awareness
CP	Cooperative Perception
DOF	Degrees of Freedom
HO	Host Vehicle (HV) to Object (O)
HV	Host Vehicle
IoU	Intersection over Union
ITS	Intelligent Transportation System
O	Object
OA	Object Age
OPQ	Object Perception Quality
POV	Principal Other Vehicle
PSM	Personal Safety Message
RO	Remote Vehicle (RV) to Object (O)
RSU	Roadside Unit
RV	Remote Vehicle
SDSM	Sensor Data Sharing Message
SV	Subject Vehicle
Unc	Uncertainty
V2I	Vehicle to Infrastructure
V2V	Vehicle to Vehicle
V2X	Vehicle to Everything
VRU	Vulnerable Road User

5. CONCEPT OF OPERATIONS

5.1 Current Situation and Problem Statement

Road safety and collision avoidance can be improved if vehicles and infrastructure exchange in a timely manner the road environment information sensed by equipped vehicles and RSUs. Equipped vehicles can sense other vehicles, pedestrians, or obstacles in their surroundings, can fuse sensor information, and can transmit and receive related road environment information from nearby vehicles and the infrastructure. The RSUs may be further equipped with enhanced data fusion and processing capabilities, such as mobile edge computing.

Each vehicle senses its surroundings with potentially a host of sensing mechanisms, which are subject to measurement inaccuracies due to noise, interference, weather, and mobile dynamics. Furthermore, each such vehicle identifies other vehicles or objects relative to its own frame of reference. That reference is based on the vehicle's position, which is subject to error, and can only be estimated with a degree of uncertainty at some given confidence. Both a transmitting RV and a receiving HV have positions and kinematics (e.g., heading, speed) subject to measurement errors, which are compounded depending on the situation. Additionally, the processing in each vehicle has its inherent cycles and the communication medium has practical bandwidth limitations, both resulting in latency in the transmitted and received data.

All these factors pose challenges that need to be addressed to ensure that CP messages exchanged are not only useful but also do not lead to an erroneous visualization of the road environment with negative consequences. The salient aspects of this multifaceted problem are introduced below in more detail.

5.1.1 Data Fusion

Vehicles participating in CP need to have the ability to fuse data received from other sources, vehicles, or infrastructure, via communication, with data generated locally from the vehicle's own sensing systems. Each stream of data may have its own attributes, including accuracy and latency, and enters into an algorithmic process to determine the best usable combination that meets the needs of the driving tasks at hand. Different levels of data fusion are possible, ranging from sharing raw measurements (e.g., point clouds) to intermediate processed data to highest level object/perception data. Different levels of fusion imply distinct levels of possible information loss and have serious implications for the needed communication among the vehicles and with the infrastructure.

5.1.2 Communication Bandwidth and Latency

Interchanging raw sensor data among vehicles implies the need for potentially vast amounts of bandwidth for reliable communication. Bandwidth is a very valuable resource, and its practical limitations can result in degraded reliability and higher latency. The communication needs have to be traded against the acceptable level of information exchanged, i.e., large amounts of raw sensor data versus medium-level or high-level processed perception data, as well as the data latency requirements of the driving tasks to be supported.

5.1.3 Computational Architecture

Data fusion strategies, coupled with communication bandwidth needs and latency constraints, can influence whether the equipped vehicles and roadside infrastructure units become the primary nodes where data fusion computations take place or if some of the computational load can be performed in the cloud or in edge computing nodes.

5.1.4 Object Sensing and Positioning Accuracy

Object detection and measurement relies on sensing as well as positioning of the vehicle equipped with the sensors. Multiplicative errors can propagate and render the communicated information unreliable, unusable, or even misleading with negative consequences. The roles, ranges, precision, and accuracy of sensors are all important. Of equal importance is the positioning of the RV or HV and level of confidence and related uncertainty it has in the accuracy of its computed position. The concepts of position uncertainty and associated level of confidence are very closely tied and critical to the viability of the solution to CP.

5.1.4.1 Accuracy, Uncertainty, and Confidence (in Determined Position)

Absolute accuracy and error-free positioning are not possible in the real world. Not only is GNSS positioning subject to measurement errors, but so are sensor-based measurements. Vehicles move, have odd, unpredictable surfaces, and many sources of microwave and light pollution exist in the road environment impacting sensing. Sensors also have their inherent measurement accuracy limitations. It should be noted that accuracy is different from precision, which pertains to the resolution with which a positioning related quantity is expressed. In some circumstances, poor sensor precision could impact and reduce accuracy.

As explained in the definition of uncertainty (see [3.14](#)), position is generally not described by a dot but by an error ellipsoid in 3D and an error ellipse in 2D. The ellipse (using 2D for simplicity) is the so-called uncertainty (or error) ellipse; it is an estimate of the accuracy (or error) of the determined position, calculated by the positioning system itself, at a certain agreed upon level of confidence, e.g., the positioning system is 90% confident that the actual position lies inside the prescribed ellipse with “a” meters semi-major axis and “b” meters semi-minor axis and some ellipse tilt angle. At times, the ellipse is further simplified to a circle. A higher required confidence naturally results in a larger uncertainty ellipse or radius. Translations exist under certain assumptions for equivalent uncertainties under different levels of confidence. This is addressed in [Appendix A](#). A uniform definition and interpretation of the uncertainty and associated confidence associated with a reported position are crucial to the proper definition of positioning accuracy, positioning requirements, and the overall operation of a CP system.

5.1.4.2 Positioning and Sensing Errors Accumulation

Errors due to the positioning system and errors from sensing accumulate and combine to limit the performance and operation of a CP system. When the errors from positioning (e.g., GNSS) are assumed to be independent from sensing errors (e.g., radar or lidar), the overall probability of correctly determining the absolute position of a detected object within a certain error bound becomes the product of the individual probabilities. This results in a higher overall uncertainty in the combined estimate at a given confidence level. In practical terms, this compounded uncertainty leads to a larger error (or uncertainty) ellipse representing the absolute position of the detected object. The absolute (i.e., not relative) error estimate is often preferred in CP because the receiving entities (e.g., other vehicles or infrastructure) do not share the same local reference frame as the reporting vehicle. Communicating absolute positions, along with associated uncertainties, enables accurate and consistent interpretation across heterogeneous systems.

A vehicle sensing an object has both a ranging error and an object angle detection error. These ranging and angular error sources in sensing can be assumed uncorrelated for simplicity (see [Appendix C](#)). However, a sensing vehicle's heading error is generally indistinguishable from its object detection angular error when relayed to another vehicle, i.e., these two sources accumulate to create an overall angular error. Ranging and angular errors toward an object accumulate with positioning errors to create larger compound errors that need to be analyzed to ensure the CP data exchanged is useful.

5.1.5 Latency

Positional accuracy and latency are interrelated. Latency can result from the nature of the communication medium where bandwidth is limited, and the channel is in some sense slotted, with some waiting for the proper instant to transmit the available data inherent to the medium. Latency also results from the fact that processing inside the vehicle is not instantaneous and has its own cycles. Furthermore, some sensors may have more latency than others, e.g., a radar may be near instantaneous, but a camera image may need time averaging to establish the presence of an object and determine its edges.

Another aspect of latency pertains to the overall positional uncertainty as it has direct impact on the time available to execute maneuvers. The confidence level used in setting the positioning uncertainty (e.g., 95% or 99%) is directly a function of the criticality of the maneuver and the kinematics of the participants. It affects the data in certain basic messages, such as red-light violation warning, or in setting up a cooperative merge. At whatever confidence level, the resulting uncertainty impacts the tolerable latency. Generally, the more positional uncertainty exists, the less latency can be accommodated.

This concept of operations report will address individually and jointly, as needed, the main challenges of positioning errors, heading errors, sensing inaccuracies, and latency impacts. This will lead to an understanding of the key parameters of this complex CP endeavor. In this process, the various user needs in those areas of challenge will be identified, thereby paving the way for subsequent development of concrete functional requirements and system design frameworks.

5.2 Local Detection

Local detection is a critical aspect of the CP process, which can be performed by either RSUs installed along the infrastructure or an RV.

Depending on the detection quality of the objects detected (see [7.6](#)), the RSU or RV assembles the data pertaining to the detected objects into CP messages and transmits those CP messages.

A recipient (an RSU or HV) can then fuse the received CP data with its own local detection data to enhance situational awareness and safety.

5.2.1 RSU Detection

As illustrated in [Figure 1](#), an RSU is equipped with infrastructure-based sensors installed along the roadside and typically includes a combination of cameras, lidar, radar, and other sensors. RSU detection provides a stationary and elevated viewpoint, allowing for comprehensive monitoring of the surrounding environment.

Advantages:

1. **Wider field of view:** RSUs are strategically placed to cover large areas, including intersections and highway segments, providing a broader perspective compared to vehicle-mounted sensors.
2. **Reduced occlusions:** Elevated positions help minimize occlusions caused by other vehicles or infrastructure, enhancing detection accuracy.
3. **Environmental resilience:** RSUs are often more robust to adverse weather conditions as they can be equipped with specialized housings and maintenance routines.

Limitations:

1. **Latency in data delivery:** Data must be transmitted from RSUs to vehicles, introducing potential latency issues.

5.2.2 RV Detection

As illustrated in [Figure 2](#), an RV (with vehicle-mounted sensors) detects and interprets the environment in real time. These units include cameras, lidar, radar, and ultrasonic sensors.

Advantages:

1. **Low latency in data delivery:** Vehicle-mounted sensors provide immediate data processing and response capabilities essential for autonomous driving.

Limitations:

1. **Limited field of view:** Vehicle-mounted sensors have a restricted perspective often affected by occlusions from other vehicles and environmental features.
2. **Sensor limitations:** Vehicle-mounted sensors are in a harsher setting and can be susceptible to environmental factors such as dirt, fog, rain, and a wet or fogged surface, which can degrade detection performance.

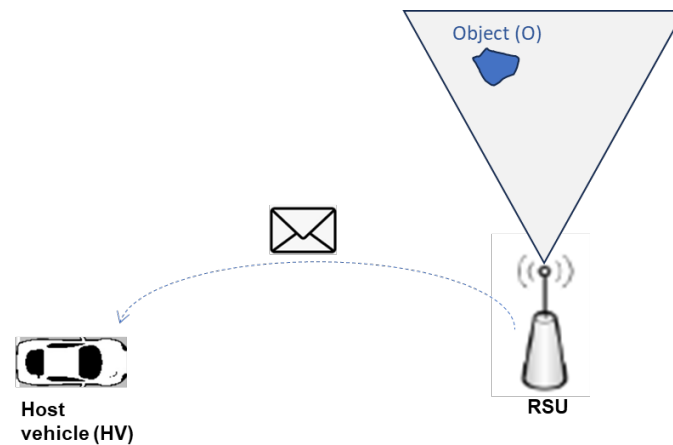


Figure 1 - Illustration of RSU detection

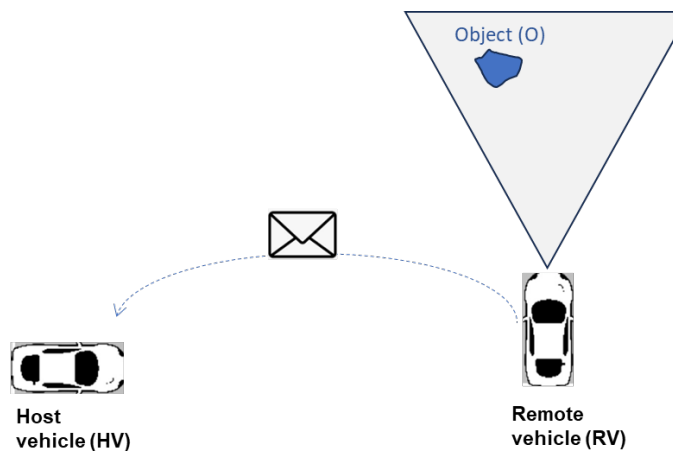


Figure 2 - Illustration of RV detection

5.3 CP Data Flow Case Descriptions

Various operational CP scenarios exist, but the data flows can generally be abstracted into fundamental cases, along with some composite variations, that collectively represent a broad spectrum of real-world CP applications.

5.3.1 Data Flow Case 1: RSU Detection and CP Data Sharing with HV

The first Data Flow Case is illustrated in [Figure 3](#) conceptually and schematically. An RSU equipped with sensing capabilities detects an object (which could be an unequipped vehicle, a VRU, or an obstacle) in its field of view and transmits a message, such as a Sensor Data Sharing Message (SDSM) defined in SAE J3224, containing information pertaining to the detected object. This message is received by the HV. The RSU is normally deployed with accurate knowledge of its position, and its positioning error is considered negligible. The first set of errors to contend with here are the errors in determining the range from the RSU to the object and the angle to the object. Additionally, the HV has its own positioning error, which will impact any maneuvers it plans to avoid collision with the object. Its heading error (not shown in the figure) could also come into play during maneuver execution. In subsequent sections, certain analytical simplifications will be used, e.g., setting certain errors to zero, to enable a step-by-step exploration of the problem.

One illustrative scenario for this Data Flow Case is a variation on the occluded pedestrian avoidance described in SAE J3251, wherein an RSU detects the VRU and relays that information to an HV approaching the occluded pedestrian. Another illustrative scenario is that described in SAE J3282 of the permissive left turn under the supervision of the infrastructure. In that case, the RSU detects the approaching vehicles and shares their information with the vehicles about to turn left. Both of these illustrative scenarios will be analyzed in [Section 8](#), after the analytical tools pertaining to the analysis of positioning and ranging errors are developed within [Section 7](#).

5.3.2 Data Flow Case 2: RV Detection and CP Data Sharing with HV

If, instead of an RSU, object detection is performed by an RV, which subsequently transmits the detected object-related information that is received by HV, an added layer of complexity results. This Data Flow Case is shown in Figure 4. RV determines its range and angle to the detected object, which creates an additional source of error since its position is subject to uncertainty, with a positioning error significantly more impactful than the negligible error had the detection been by an RSU. The RV transmits a message containing information about the detected object, along with its own position, which serves as the reference frame for that object. This message is received by the HV. The positioning errors at both the RV and HV are thus compounded at HV. This is in addition to the object sensing and object angle detection errors. If RV also has a heading error, at HV it becomes indistinguishable from the object angle detection error, i.e., the observed angle error due to the RV-object combination is a composite error of object detection angle and heading error at RV.

The first illustrative scenario for this Data Flow Case is the standard occluded pedestrian avoidance situation described in SAE J3251, wherein a large vehicle, e.g., trailer truck, detects the VRU about to cross the street and relays its information to an HV approaching somewhat behind the truck, occluding the VRU from it. Here the object detection errors at the truck and the positioning errors at the truck (the RV) and the HV all affect the distance needed for HV to stop safely before the pedestrian. The second illustrative scenario for this Data Flow Case is again the permissive left-turn lane in SAE J3282, where the following vehicle approaching the intersection detects the vehicle ahead of it closer to the intersection and shares the pertinent information about both approaching vehicles with the vehicles about to turn left. Analysis of these two illustrative scenarios will also be provided in [Section 8](#).

5.3.3 Data Flow Case 3: RV Detection and CP Data Sharing with RSU

This case is illustrated in [Figure 5](#). The RSU contributes significantly less error than HV in the chain of elements involved in the detection and information dissemination process. The RSU can use the information it received to issue traffic commands or advisories or be part of the composite CP Data Flow Cases, where subsequent CP data propagation is performed, as in [5.3.4.2](#).

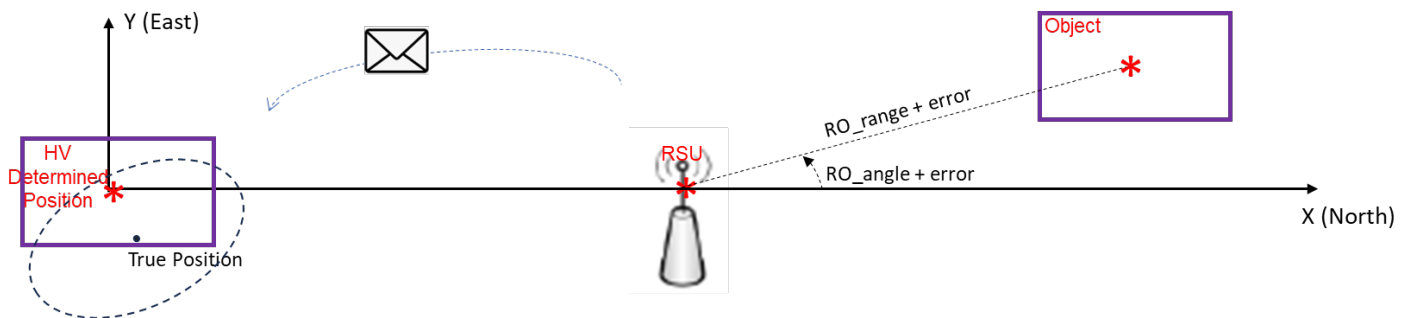


Figure 3 - Data Flow Case 1: RSU detection and CP data sharing with HV

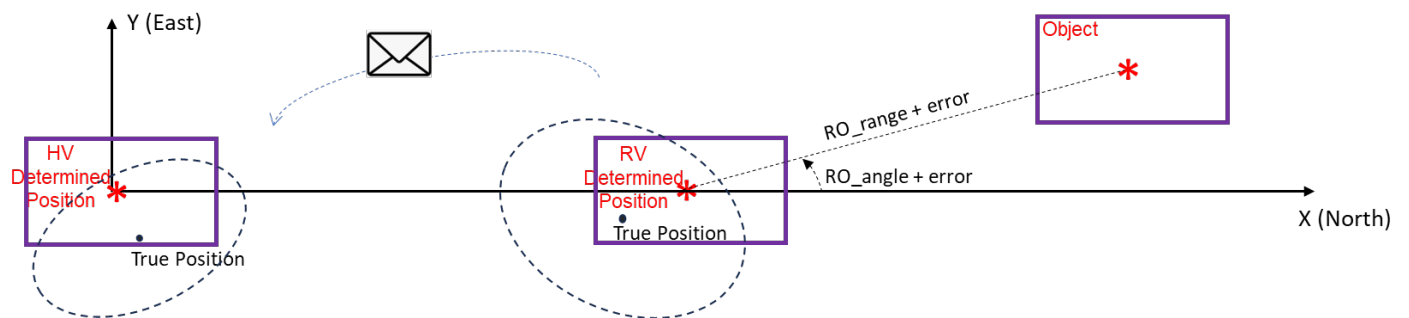


Figure 4 - Data Flow Case 2: RV detection and CP data sharing with HV

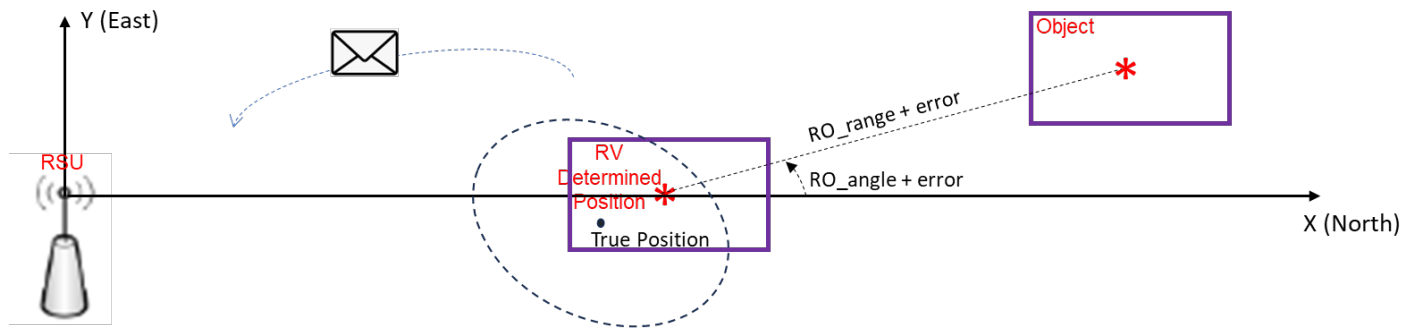


Figure 5 - Data Flow Case 3: RV detection and CP data sharing with RSU

5.3.4 Composite Cases

5.3.4.1 RSU-HV plus RV-HV Case

In this case, an RSU senses an RV (or an object sensed by RV) and sends its info, possibly after fusion either locally or in the cloud, which HV receives. HV also receives data from RV directly. HV fuses data from both streams to attempt better object perception.

5.3.4.2 RV-RSU/Infrastructure-HV Case

This case adds onto Data Flow Case 3 (see [5.3.3](#)). Here vehicles transmit their perception data to the infrastructure that is likely connected to MEC, which performs fusion on the information received in these V2I messages together with data detected by the infrastructure. The infrastructure/RSU then sends the fused information to nearby vehicles.

5.4 Motion Model Considerations

Full 3D Motion Model

To fully describe the kinematic and attitude state of a vehicle or detected object, a 6-DOF (degrees of freedom) motion model should be used (refer to CAR2CAR-2089). This 3D motion model includes 18 parameters:

Nine Translational Parameters:

- Position (x, y, z)
- Velocity (vx, vy, vz)
- Acceleration (ax, ay, az)

These parameters capture all linear (translational) degrees of freedom, describing where the vehicle or object is, how fast it is moving, and how quickly that speed is changing in 3D space.

Nine Rotational (Attitude) Parameters:

- Orientation angles (roll, pitch, yaw)
- Angular rates (rollRate, pitchRate, yawRate)
- Angular accelerations (rollAcceleration, pitchAcceleration, yawAcceleration)

These parameters capture the vehicle or object's rotation in 3D space, how fast it is rotating, and how those rotation rates are changing over time.

Simplified 2D Motion Model

For most passenger vehicle applications in structured road environments, the motion can be sufficiently modeled in two dimensions. The simplified 2D model describes the state of a vehicle using planar position (x , y), heading ϕ (yaw)¹, and, optionally, speed and acceleration in the plane. Roll and pitch are neglected, and the vertical position z is either assumed constant or irrelevant to the task. This model supports compact representations of uncertainty (e.g., 2D uncertainty ellipses) and aligns with common mapping and localization approaches in transportation systems.

The following nine-parameter state vector is commonly used in 2D motion modeling for typical on-road passenger vehicle scenarios:

1. xPosition - Longitudinal (forward) position
2. yPosition - Lateral (sideways) position
3. xSpeed - Longitudinal speed
4. ySpeed - Lateral speed
5. xAcceleration - Longitudinal acceleration
6. yAcceleration - Lateral acceleration
7. yawAngle - Heading angle around the z-axis (vertical)
8. yawRate - Yaw (heading) angular rate
9. yawAcceleration - Yaw (heading) angular acceleration

This simplified 2D motion model is appropriate for ground-based CP applications and is adopted for evaluating the CP system involving vehicles and objects in this report. Depending on the scenario at hand, a subset of these parameters may not enter into the analysis.

As noted in [10.7](#) and [11.4](#), a 3D motion model is recognized as important for scenarios involving elevated roads and aerial platforms and is recommended for future extension and/or clarification in SAE J3224.

5.5 Coordinate System Considerations

As derived in [Appendix D](#), the local-to-local frame transformation is inherently non-linear. Representing a detected object in a local frame and subsequently transforming from one local frame to another adds not only computational overhead but also complexity. In contrast, the SDSM defined in SAE J3224 reports detected objects as follows:

- Object offsets relative to a reference position within an Earth-fixed coordinate system.
- The reference position of either an RV or RSU is specified in the WGS84 coordinate frame.

Additionally, speed and heading are defined in SAE J3224 as follows:

- Heading is measured relative to the X-axis (North) within an Earth-fixed coordinate system.
- Speed is also defined with respect to an Earth-fixed coordinate system.

¹ For a typical passenger vehicle operating on normal roads with negligible lateral motion, the longitudinal axis of the vehicle body closely aligns with its actual travel path. Under such conditions - absent significant skidding, crosswinds, or drift - the vehicle's yaw angle (its body orientation) and heading (the direction of motion in global coordinates) effectively become equivalent.

As shown in [5.2](#) and [5.3](#), the 2D motion model is adopted for HV, RV/RSU, and Object, and an Earth-fixed coordinate system is employed to evaluate the impacts of individual error sources and the manner in which errors accumulate. In other words, the Earth-fixed coordinate system applies to evaluation and analysis in later sections.

This global coordinate-based approach provides a clear, intrinsic understanding of individual errors and their accumulation without introducing additional complexities or skew arising from local frame transformations. A comparison between this approach and a recent method involving local frame transformations is presented in [11.2](#).

5.6 Summary

Subsection [5.1](#) presents key challenges associated with CP systems. Object detections by RSUs and RVs are described in [5.2](#), while typical CP data flow cases - representing a wide range of real-world applications - are outlined in [5.3](#). Considerations related to motion models and coordinate systems are discussed in [5.4](#) and [5.5](#), respectively.

[Table 1](#) provides a mapping summary that links the topics introduced in this section to the corresponding sections where they are addressed in greater detail.

Table 1 - Summary of section references for key CP topics

Topics	Evaluated	Sections
CP System Architecture	CP system reference architecture	6
Data Fusion and Perception Level		7.1
2D Motion Model for Vehicle or Detected Object		
1. xPosition – Longitudinal (forward) position	Position accuracy and uncertainty	7.2.1 for RV and HV 7.2.2 for Object
2. yPosition – Lateral (sideways) position		
3. xSpeed – Longitudinal speed	Speed / positioning impact on timing; Additionally, relative speed between HV and O impacts the position error induced by CP latency	7.3 See 7.4.3
4. ySpeed – Lateral speed		
5. xAcceleration – Longitudinal acceleration	Addressed indirectly through its impact on speed and position	
6. yAcceleration – Lateral acceleration		
7. yawAngle – Heading angle around the z-axis (vertical)	Heading accuracy and uncertainty	7.2.3 for RV and HV
8. yawRate – Yaw (heading) angular rate	Addressed indirectly through its impact on yawAngle (heading)	
9. yawAcceleration – Yaw (heading) angular acceleration		
CP Latency	Timing accuracy and uncertainty	7.4
Object Detection	Detection accuracy and uncertainty	7.6 for IoU 7.7 for object perception quality
Performance Needs Assessment Framework		7.7
Uncertainty Analysis - Analytic	CP scenario evaluation	
Basic tool and approximation methods		7.2.4 and 7.2.5
Illustrative scenarios		8
IoU and Uncertainty Analysis - Simulation	CP scenario evaluation	9
Shared Data Types	Evaluation	10
Conclusions and Recommendations	Summary	11

6. REFERENCE ARCHITECTURE

[Figure 6](#) illustrates the generic architecture of the CP system with its communication interfaces and abstracted key subsystem elements, which are described in more detail in the following subsections.

The salient takeaway is that each entity, whether an RV or HV² or RSU, has sensing and communication modules connected internally to one or more control and processing units. Additionally, vehicles have positioning subsystems, which are typically GNSS-based augmented with inertial components. On the other hand, RSUs may be connected to cloud services or MEC platforms. To support interoperability and consistent implementation, the messages that flow over the V2X interfaces need to be described and subsequently their contents defined and standardized.

NOTE: A reference architecture for CP focuses specifically on sharing detailed sensor-derived data about the surrounding environment (like detected vehicles, pedestrians, and obstacles). As pointed out in the definition of CP ([3.3](#)), this is distinct from Cooperative Awareness (CA), which involves broadcasting only the transmitting entity's own state (e.g., position, speed), as seen in Basic Safety Messages (BSMs) from equipped vehicles or Personal Safety Messages (PSMs) from equipped VRUs. Because CA messages do not contain environmental perception data, they serve a fundamentally different purpose. Therefore, incorporating CA into a CP reference architecture would blur the boundaries and unnecessarily complicate the architecture, making it less clear and efficient.

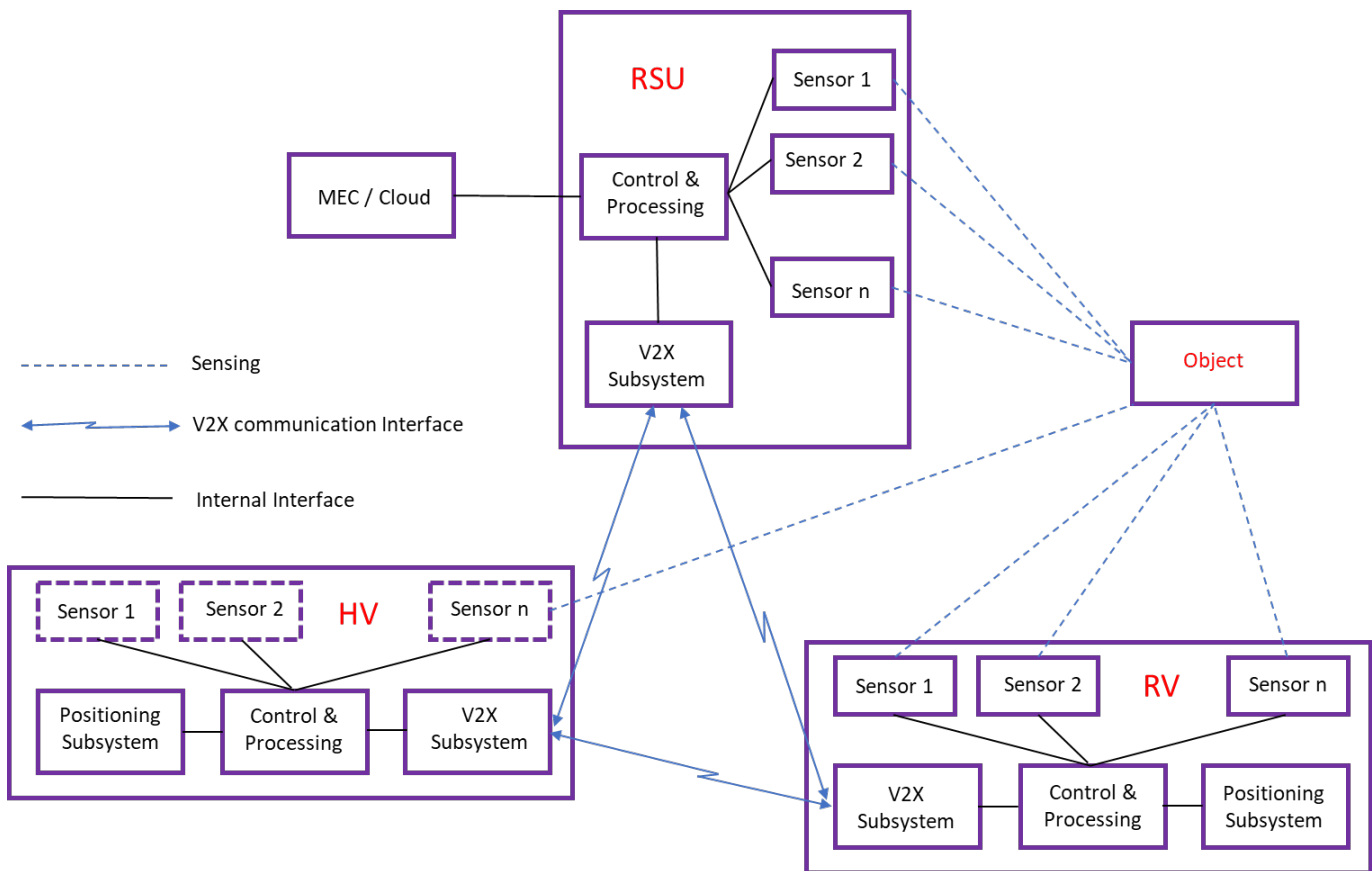


Figure 6 - Reference architecture for cooperative perception

² HV sensors are optional components in the CP system, as indicated by the dashed box in [Figure 6](#). When the HV is equipped with onboard sensors, it can perform sensor fusion by integrating its own sensing data with information received via V2X. Otherwise, the HV relies solely on V2X-based sensing information for extended perception.

6.1 Architecture Elements

6.1.1 Equipped Vehicles (HV and RV)

Vehicles actively participating in CP are generally equipped with Advanced Driver Assistance Systems (ADAS) or Automated Driving System (ADS) comprising onboard sensing technologies and V2X communication capabilities to interact with and exchange low latency information with other equipped vehicles and the infrastructure. Vehicles with ADAS or ADS have sensors; the ones most applicable to CP are introduced in [6.1.6](#).

6.1.2 Roadside Infrastructure Unit (RSU)

Elements of the roadside infrastructure supporting CP may entail RSUs with both sensors and communication capabilities. RSU detection provides a stationary and elevated viewpoint, allowing for comprehensive monitoring of the surrounding environment, particularly at intersections or work zones, compared to vehicle detection. V2X depicted in Figure 6 is among the possibilities to support the communication needs of CP.

6.1.3 V2X Communication Network

A low latency, high bandwidth network (for example, a 4G- or 5G-based V2X), a more advanced network, or even a hybrid network with other lower protocol layers would be the medium through which the wealth of messages is exchanged among the vehicles and to/from the infrastructure. This could also include information exchange with the cloud and/or edge processing nodes, which collectively enable CP.

6.1.4 MEC/Cloud

In a most general form, not all the computational power to support the processing of possible point cloud sensor data need be housed in the vehicle or on the roadside. When communication bandwidth permits, part of the processing workload can be off-loaded to cloud-based systems. However, to reduce network congestion and improve responsiveness, Mobile Edge Computing (MEC) platforms can be deployed closer to the data source.

MEC offers several advantages:

- Reduced communication load compared to full cloud off-loading.
- Lower latency, enabling faster perception and decision-making.
- Enhanced reliability through localized processing and reduced dependency on wide-area networks.

By integrating MEC or cloud computing resources, cooperative perception systems can better manage computational demands while maintaining timely and reliable performance.

6.1.5 Object (Unequipped Vehicle, Unequipped VRU, Obstacle)

An Object refers to any entity detected in the traffic environment by equipped vehicles or roadside infrastructure units. Objects may include unequipped vehicles (vehicles lacking sensing or communication capabilities), unequipped VRUs (such as pedestrians, cyclists, or wheelchair users), and static obstacles (such as road debris or fallen cargo). Each Object's position, speed, heading, size, and associated uncertainties are perceived and communicated within the CP system to enhance environmental awareness and improve transportation safety and efficiency.

6.1.6 Vehicle and Infrastructure Sensors

A wide range of sensors exist in modern vehicles, including some that perform internal mechanical functions necessary for executing driving tasks safely and efficiently while providing the driver with useful or critical information. The focus here is on those sensor types that would be most engaged in CP. [Figure 7](#) provides a visualization of the ranges, functions, and overlap of the key sensor types.

The sensors in an ADAS or ADS vehicle work in concert and through data fusion create a comprehensive model of the environment surrounding the vehicle.

6.1.6.1 Radar

Typically, in the millimeter wave range and can be used for either long-range tasks like adaptive cruise control or closer-in functions like blind spot object detection, rear cross traffic alert, or lane change support.

6.1.6.2 Lidar

Laser pulses to detect and measure range to an object and, in more sophisticated implementations, can be used to create a 3D mapping (point cloud) of the surrounding environment, including objects like buildings, vehicles, and pedestrians.

6.1.6.3 Cameras

Cameras can provide either directional or surround view of the environment, enabling object detection and avoidance and a host of varied functions like traffic sign recognition and lane departure warning.

6.1.7 Positioning

Usually based on GNSS, which could be augmented with differential corrections and inertial navigation sensor inputs and map matching.

6.2 Architectural Needs and Preconditions

- Each equipped vehicle has at least one communication device that allows data to be transferred between such vehicles and with the infrastructure.
- Each equipped vehicle is capable of transmitting messages with data elements using communication devices, protocols, and interfaces.
- Each equipped vehicle has a positioning system that is able to report a position and position error estimates (uncertainty) at an agreed upon level of confidence.
- Each equipped vehicle has a sensor suite, a processor with logic that can combine and fuse sensed data with that received from other equipped vehicles, and a planning algorithm that can affect vehicle maneuvers.
- Not all processing needs to occur at the vehicle - various mobile edge computing and cloud-based architectures are possible options.



7.1 Data Fusion and Perception Level

As described above, modern vehicles have an increasingly wide range of onboard sensors. Fusion of data from these diverse systems within the vehicle and its sharing among vehicles is an essential element of CP. The more fusion of such data achieved the better, and more accurately, the vehicle will perceive its surrounding environment. There are different levels of sensor data processing and sharing that the system architecture needs to be able to support, depending on the trade-off between wealth of information shared and high demands on the communication medium. Adapted from Bai et al. (2022), the level of sensor data fusion can be broadly classified as early, middle, or late data fusion as described below and illustrated in [Figure 8](#).



7.1.1 Early/Sensor Data Fusion

Raw sensor data such as images or lidar point clouds containing complete information about the vehicle's detected surroundings could be shared, but such intensive information sharing requires very large communication bandwidth and costs, which depending on the communication medium may not be feasible.

7.1.2 Mid/Deep/Feature Level Data Fusion

This level of data fusion entails sharing intermediate representations (for example, edges, textures, surfaces, etc.). It requires algorithms in the vehicle to identify and extract the salient features in its surrounding environment. Similar features from sensors could be fused and tracked. This level of presentation attempts to retain critical information while achieving a better performance-transmission trade-off.

7.1.3 Object Level/Late Data Fusion

This level of fusion entails merging information from multiple sensors to a higher level of abstraction, combining results from multiple algorithms, and making decisions on sensed objects prior to sharing that information. For example, input images may be processed individually to extract critical information within them and decision rules subsequently applied prior to sharing. This is the most transmission-efficient level of sharing, but some valuable information will be lost depending on the needed level of cooperation.

Each fusion scheme has its own advantages and disadvantages depending on the context. Early fusion and deep fusion offer higher accuracy but require more computational power and complex model design. In contrast, late fusion can achieve better real-time performance but may sacrifice some accuracy. The optimal fusion scheme depends on the specific demands of different traffic scenarios. For example, consider the data rate required for processing lidar point clouds, as discussed in Yu et al. (2023): Early fusion requires a data rate of 13 megabytes/s (MB/s), mid-fusion requires 0.62 MB/s, and late fusion only requires 3.3 kB/s. More performance comparisons among different fusion schemes via simulations can be found in Wang et al. (2020) and Hu et al. (2024).

Given that late fusion provides a balanced trade-off between fusion performance and communication bandwidth, object-level/late fusion is the primary focus of this information report.

7.2 Positioning Accuracy Needs

It is crucial to understand how individual error sources in a CP system impact overall system performance. This section begins by examining the effects of vehicle position error (see [7.2.1](#)), object sensing error (see [7.2.2](#)), and vehicle heading error (see [7.2.3](#)). Additionally, the impact of CP latency is explored in [7.4](#).

Subsection [7.2.4](#) introduces an uncertainty scaling tool, while [7.2.5](#) provides approximation methods through the following subsections:

- [7.2.5.1](#): Uncertainty Ellipse Approximation
- [7.2.5.2](#): Relative Positioning Error Approximation Using Variances
- [7.2.5.3](#): Error Accumulation Approximation

Together, [7.2.4](#) and [7.2.5](#) enable comprehensive uncertainty analysis across multiple scenarios, as demonstrated in [Section 8](#), to support effective error analysis in guiding system design.

7.2.1 Vehicle Positioning and Error Estimation

Positioning in the real world is never perfect. It is impacted by noise, multipath, shadowing, interference and timing offsets, and, if applicable, inertial sensor drift issues. A positioning engine generates the determined position along with an estimate of its accuracy, described by the positioning uncertainty. The uncertainty traces a contour within which the positioning system believes the true position lies with a certain level of prescribed probability or confidence. In 3D systems the uncertainty traces an ellipsoid, and in 2D systems this reduces to an ellipse, commonly referred to as the error ellipse. This ellipse is illustrated in [Figure 9](#), which has a semi-major axis of “a” and semi-minor axis of “b” and tilt angle “theta.” The directions of these axes are those of the eigenvectors of the covariance matrix of the positioning error. The values of “a” and “b” are the corresponding scaled eigen values and the level of confidence for which the ellipse is computed. If the errors in the two directions are uncorrelated, the tilt becomes zero.

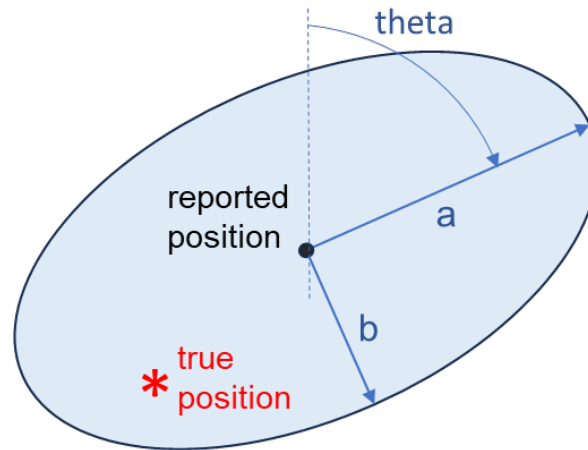


Figure 9 - Uncertainty (error) ellipse in 2D positioning systems

Normal distribution arguments are often made to try to obtain familiar or standardized levels of confidence associated with uncertainty. The normal distribution of error along the two axes of the horizontal plane are often justified via the central limit theorem if there are various independent sources of error, for example, due to satellite motion, ionospheric effects, noise, multipath, etc., i.e., based on the physics of the problem.

Using the normal distribution in each of the X and Y directions, e.g., North and East, the horizontal error estimate follows a Chi-squared distribution with two degrees of freedom. In each of the X and Y directions simple normal distribution characteristics can be applied. For example, the probability that the error in X direction P_x is less than its standard deviation σ_x is 68%, 95% for $2\sigma_x$, and 99.7% for $3\sigma_x$. Although similar behavior would apply for the error in Y relative to σ_y , the joint probability that a two-dimensional positioning error (i.e., the error in the horizontal plane) is less than a certain number is actually derived from the joint distribution.

This is illustrated well by a popular ellipse, the so-called “1-sigma ellipse” or “standard error ellipse.” It is the uncertainty ellipse whose semi-major axis is σ_x and semi-minor axis is σ_y . The probability that the positioning error is within this standard ellipse (the confidence) is not 68% but rather 39.4%. For 2-sigma it is 86.5%, and it is 98.9% for 3-sigma. The 95% ellipse (i.e., 95% confidence the actual position is within that ellipse) is the 2.45-sigma ellipse. The key interesting values of error probabilities are summarized in Table 2. It is interesting to see from the table that the commonly quoted 68% has no specific role to play in a 2D positioning error.

Table 2 - Key probability values for positioning error in the horizontal (X-Y) plane

One Dimensional (x & y) Sigma Multiple	Probability in the x-y Plane	Notation
1.00	39.4%	1-sigma or "standard" ellipse
1.18	50.0%	Circular Error Probability (CEP)
1.414	63.2%	Distance RMS (DRMS)
2.00	86.5%	2-sigma ellipse
2.45	95.0%	95% confidence level
2.818	98.2%	2 DRMS
3.00	98.9%	3-sigma ellipse

The subtle but very important distinction between accuracy along an axis and accuracy in the horizontal plane has critical ramifications for the definition of vehicle positioning requirements. Absolute vehicle positioning is not a one-dimensional problem, and if altitude errors are ignored, it is a two-dimensional problem.

A 68% confidence level is generally considered too low for reliable performance assessment, while a 99% confidence level may be overly conservative and extend beyond the practical bounds of Gaussian distribution approximations. A 95% confidence level, on the other hand, is widely recognized as a standard benchmark across various domains - such as engineering, GNSS specifications (e.g., RTK, GPS), and hypothesis testing - ensuring consistency and comparability among systems and vendors.

Therefore, it is **recommended** that position accuracy be specified at a 95% confidence level. Although the confidence and uncertainty transformations provided in [Appendix A](#) can be applied as a work-around solution, a clear and unambiguous definition for these quantities is needed for CP applications.

The analysis for the relative position error and approximation between two vehicles can become complicated and is addressed in [7.2.5.2](#).

7.2.2 Object Range and Angle Detection Errors

The assessment of error contribution from sensing an object by the RV takes a somewhat different analytical approach from that of chi-squared, necessitated by the distinct underlying physics. Typically, an object is detected using sensors such as radar, lidar, or cameras or through a multi-sensor fusion approach. As discussed in [Appendix C](#), it is reasonable, for simplicity, to assume that the object ranging error and angular error are zero-mean, uncorrelated random variables.

As illustrated in [Figure 10](#), the detection of the object O takes the form of determining a range RO and an angle from north ϕ_{RO} . Due to sensing inaccuracies and measurement noise, the object appears as O^* at a range RO^* and angle ϕ_{RO}^* from north. The errors in the estimated range and angle to the object are ΔRO and $\Delta \phi_{RO}$. Statistics of these errors are not the same as those in positioning, which is heavily influenced by GNSS and its normally distributed error components in X and Y, yielding the convenient chi-square error uncertainty. The objective here is to use the sensing system's error estimates for ΔRO and $\Delta \phi_{RO}$, namely σ_{RO}^2 and $\sigma_{\phi_{RO}}^2$, to derive the error statistics in the universal reference direction X (North) and Y (East), i.e., the statistics of Δx_{RO} and Δy_{RO} , denoted by the variances $\sigma_{x_{RO}}^2$ and $\sigma_{y_{RO}}^2$.

Since the errors ΔRO and $\Delta \phi_{RO}$ are not large, this enables the application of a good Taylor Series approximation for the error, where the first derivative terms only are retained yielding:

$$\Delta y_{RO} = \Delta RO \sin \phi + RO \Delta \phi_{RO} \cos \phi \quad (\text{Eq. 1})$$

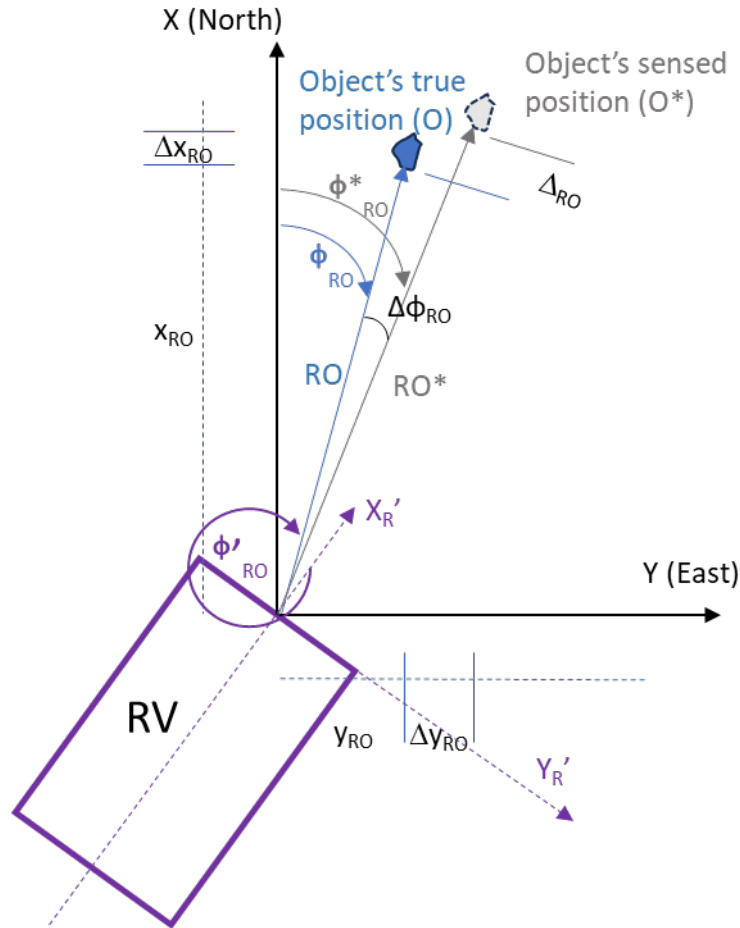


Figure 10 - Object detection and its measurement errors

Since Δ_{RO} and $\Delta\phi_{RO}$ are zero mean, the variance of y_{RO} is the mean squared value of its error, $E\{\Delta y_{RO}^2\}$, i.e., the mean of the square of the right-hand side of Equation 1. Furthermore, since Δ_{RO} and $\Delta\phi_{RO}$ are uncorrelated, the cross product of the terms in the mean square of the right-hand side is zero. This then simplifies to:

$$\sigma_{y_{RO}}^2 = \sigma_{RO}^2 \sin^2 \varphi + RO^2 \sigma_{\phi_{RO}}^2 \cos^2 \varphi \quad (\text{Eq. 2})$$

In an analogous manner:

$$\Delta x_{RO} = \Delta_{RO} \cos \varphi - RO \Delta\phi_{RO} \sin \varphi \quad (\text{Eq. 3})$$

Which gives:

$$\sigma_{x_{RO}}^2 = \sigma_{RO}^2 \cos^2 \varphi + RO^2 \sigma_{\phi_{RO}}^2 \sin^2 \varphi \quad (\text{Eq. 4})$$

Equations 2 and 4 indicate that although Δ_{RO} and $\Delta\phi_{RO}$ are uncorrelated, Δx_{RO} and Δy_{RO} are correlated. However, when the angle φ is small, Δx_{RO} and Δy_{RO} become nearly uncorrelated, as further discussed in [8.1](#).

Equations 2 and 4 also show that because of the compounding effect of the angular error with the range measurement, the distance error variance increases quadratically with the range. This increase is intuitive, since the error angle causes a longer arc at a larger range to the object.

With the standard deviation of the ranging error σ_{RO} and the angular measurement error $\sigma_{\phi_{RO}}$ determined by the RV's sensing system, it is possible to obtain the variances of their error contribution to the overall positioning and sensing error via Equations 2 and 4 and the variance in the measurements of HR along the X and Y directions (due to positioning errors at HV and RV). This will be analyzed in [8.2](#).

An alternate analytical approach, if desired, is to express the variances in sensing the object along the local frame of reference of RV, i.e., relative to X'_R and Y'_R shown in [Figure 10](#). In this case, the angle ϕ'_{RO} replaces the angle ϕ_{RO} in Equations 1 through 4. These can then be written as:

$$\Delta y'_{RO} = \Delta_{RO} \sin \phi' + RO \Delta \phi_{RO} \cos \phi' \quad (\text{Eq. 5})$$

$$\Delta x'_{RO} = \Delta_{RO} \cos \phi' - RO \Delta \phi_{RO} \sin \phi' \quad (\text{Eq. 6})$$

And the variances along the local RV frame of reference as:

$$\sigma_{y'_{RO}}^2 = \sigma_{RO}^2 \sin^2 \phi' + RO^2 \sigma_{\phi_{RO}}^2 \cos^2 \phi' \quad (\text{Eq. 7})$$

$$\sigma_{x'_{RO}}^2 = \sigma_{RO}^2 \cos^2 \phi' + RO^2 \sigma_{\phi_{RO}}^2 \sin^2 \phi' \quad (\text{Eq. 8})$$

$\Delta x'_{RO}$ and $\Delta y'_{RO}$, if provided as measurements from RV, can be used after the coordinate transformation provided in [Appendix D](#) to derive the composite positioning and sensing errors Δx_{HO} and Δy_{HO} between an HV and the object (O).

7.2.3 Vehicle (RV and HV) Heading and Error Estimation

Object range and angle detection errors are presented in [7.2.2](#). A simplified view of the object angular error impact is illustrated in [Figure 11](#). The angular error has a significant impact as it induces an object position offset error:

$$RO_range * \sin(RO_angle \text{ error})$$

- This position offset error increases linearly with RO_range.
- This position offset error increases linearly with RO_angle error (when RO_angle error is small).

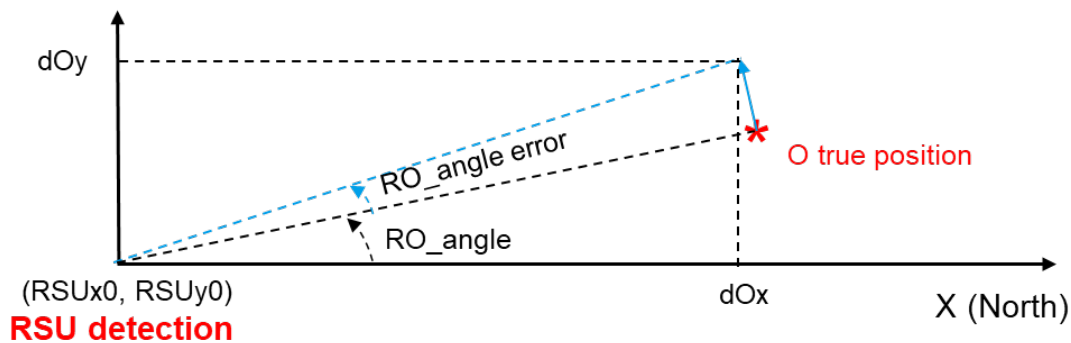
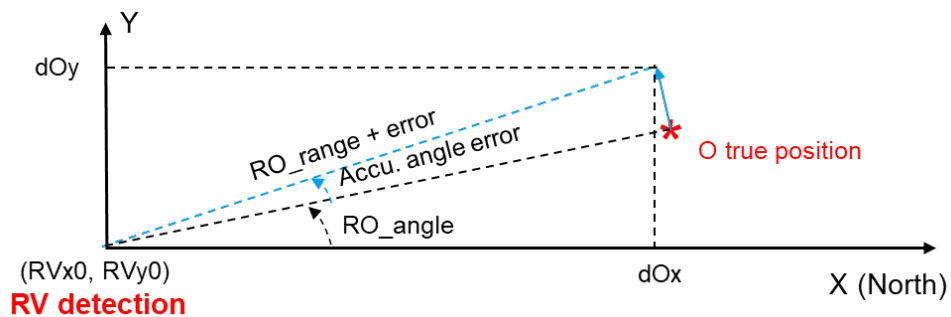
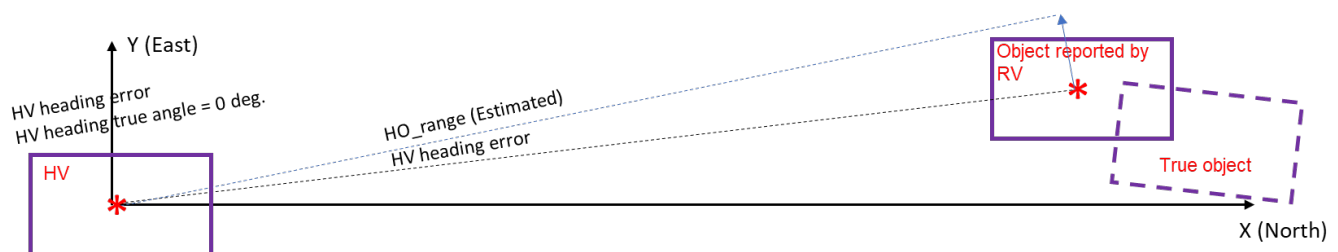


Figure 11 - A simplified view of the object angular error impact

[Table 3](#) shows the object position offset errors, given fixed angular errors with detection range 20 m and 40 m, respectively. The angle error should be <2 degrees, as 2 degrees induces a 1.4-m position offset error at a detected range of 40 m.

Table 3 - Object position offset errors given fixed angular errors

Accu. angle error (degrees)	RO_range (m)	Object position offset error (m)
0.125	20	0.0436
0.25	20	0.0873
0.5	20	0.1745
1	20	0.3490
2	20	0.6980
4	20	1.3951
6	20	2.0906
8	20	2.7835
0.125	40	0.0873
0.25	40	0.1745
0.5	40	0.3491
1	40	0.6981
2	40	1.3960
4	40	2.7903
6	40	4.1811
8	40	5.5669

**Figure 12 - A simplified view of RV heading error impact****Figure 13 - A simplified view of HV heading error impact**