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SP1 – SAFEPROBE

Data-fusion Specifications

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Abbreviation List

SF	Safe-Spot
CV	Constant Velocity
CA	Constant Acceleration
DA	Data Association
UE	Uncertainty Estimation
OM	Object Maintenance
PF	Particle Filter
BT	Bayesian Theorem
BI	Bayesian Inference
FL	Fuzzy Logic
NN	Nearest Neighbour
KF	Kalman Filter
SW	Software
HW	Hardware
CL	Central-level Fusion
TC	Tracking and Classification
LR(M)	Lagrangian Relaxation (Method)
IN(s)	Input(s)
OUT(s)	Output(s)
UKF	Unscented Kalman Filter
DS(T)	Dempster-Shafer (Theory)
PDF	Probability Density Function
ANN	Artificial Neural Networks
GRS	Geodetic Reference System
CRS	Cartesian Reference System
PF2	ProFusion2
LDM	Local Dynamic Map
SDF	Sensor Data-fusion
LRR	Long Range Radar
V2V	Vehicle-to-Vehicle
CRS	Co-ordinate Reference System
VRS	Vehicle Reference System

SRS	Sensor(s) Reference System
IPM	Information Provider Module
ROI	Region Of Interest
DAM	Data Acquisition Module
TSA	Time and Spatial Assignment
Long	Longitude
Lat	Latitude
GPS	Global Positioning System
IP(U)	Image Processing (Unit)
OR(M)	Object Refinement (Module)
SR(M)	Situation Refinement (Module)
JPDA	Joint Probabilistic Data Association
SFOS	Sensor-level Fusion for On-board Sensors
UKCM	Uniform K-Centralized Mean
COP-DF	Co-operative Pre-data-fusion
PReVENT	Preventive and Active Safety Applications
4D/RCS	4 Dimensional / Real-time Control System

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EXECUTIVE SUMMARY

The aim of this document is to describe a general description of the specifications for the data-fusion task, carried out in SAFEPROBE project. Data-fusion algorithms are developed depending not only on the particular goal to reach, but also on several factors, such as: the type of vehicles and equipment considered, the external conditions encountered, the information really available and so on. In this context, it is also important to highlight the importance to transmit together with the object or the road information, also some other specific information, like speed limit for a particular road, the typology of the vehicle (truck, car or motorcycle), etc. This approach sounds quite new respect to the current state of the art. As a good synergy with the IP PREVENT, these data-fusion specifications take into account also the recommendations and the work done in the PReVENT sub-projects “ProFusion1” and “ProFusion2”. The approach is based on the Joint Directors Laboratories (JDL), Data Fusion Model, as it partitions the fusion process into four distinct levels, providing a very structured framework.

This document centres on Object and Situation Refinement, the former combines features, location and object classification to achieve reliable representation of individual objects, whilst the later fuses data to extract relationships, behaviours and trajectories. That is, knowledge of what is around the vehicle, it is also known as Situational Awareness. Each of these modules is made of several sub-modules. Object Refinement includes Sensor Level Fusion for vehicle onboard sensors, Co-operative Pre Data Fusion to facilitate information extraction by the laser scanner, and Central level Fusion, which outputs information on the tracked objects and the results of the distributed data fusion process from information originating in the VANET. Situation Refinement is achieved in two main sub-modules, namely the Ego-Vehicle which estimates the dynamics/kinematics of the ego-vehicle[1] including trajectories, predicted manoeuvres, assessment of the driver intention, etc. It also extracts information on whether the objects are moving or stationary as well as parameters that characterise traffic conditions.

To address this estimation and distributed data fusion problem, the most used and update algorithmic techniques are included, such as Kalman Filtering for tracking and temporal alignment; Evidence and Probability Theory for data fusion and association; Combinatory Rules of Dempster for manoeuvre identification; and so on.

This deliverable illustrates therefore, the main data-fusion topics, developed inside the SAFEPROBE project of the IP-SAFESPOT. In particular the approach, and rationale behind, the algorithms chosen to implement the data-fusion for whole SAFESPOT system.

[1] In this document, with “ego-vehicle” or “ host-vehicle” is intended the prototype vehicle on which the SAFEPROBE system is installed.

1. Introduction

The aim of this document is to describe the specifications for the data-fusion task, within the SAFEPROBE project.

Data-fusion algorithms will be developed depending not only on the specific goal to reach, but also on several factors, such as: the type of vehicles and equipment considered, the external conditions encountered, the information coming from communications links and so on. In this context, it is also important to highlight the importance to transmit together with the object or road information other specific information, like for example speed limits for a particular road, the vehicle typology (e.g. truck, car or motorcycle). This approach sounds quite new with respect to the current state of the art.

This data-fusion specifications takes into account the recommendations and the work done in the IP-PReVENT sub-projects “ProFusion1” and “ProFusion2” as a good synergy with previous efforts within work sponsored by the EC.

1.1. Innovation and Contribution to the SAFESPOT Objectives

Under a certain point of view, the data-fusion topic is the “core” activity inside SAFEPROBE, one of the subprojects of SAFESPOT IP; in fact, the aim of DF is to provide an enhanced perception of the external environment, being able to put together information coming from different informative sources (both from on-board sensors and from external factors, like communication from other cars) and – based on that – to reconstruct the external scene inside the safety margin zone (as defined by the sub-project SCOVA, see [48] for more details). Therefore, the DF is expected to provide reliable information on the object dynamics and type, on prediction of host-vehicle path, on estimation of future object trajectories, etc. This information will be added on the Local Dynamic Map, in order to be available for all functions and applications requiring it.

1.2. Methodology

In developing the data-fusion issues, the starting point is a review of the state of the art, with particular attention to those projects already dealing with these topics (such as PROFUSION2). Based on these assumptions, the most appropriate architecture has been selected, that is the JDL modified in accordance with automotive domain (see chapter 2.1 of this document for more details). Furthermore, this survey helps also to define and select the most appropriate techniques and algorithms to perform the data-fusion activity, related to its different tasks (for example: Bayesian Theory for data association, Kalman Filter for tracking, etc.).

The approach to drawing up the specifications on data-fusion follows the requirements phase. The underlying methodology is based on the process set out in the European ITS Framework Architecture:

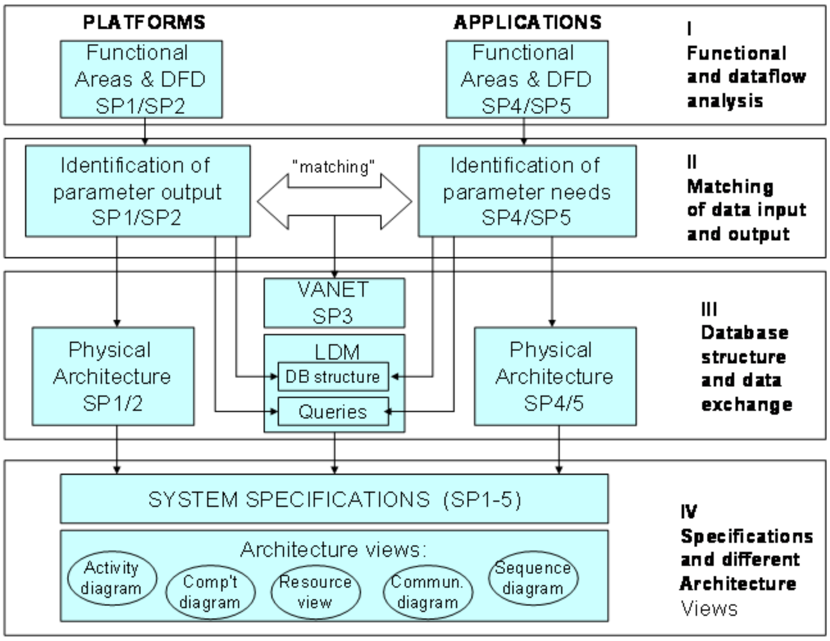


Figure 1: Methodology Used for Developing the Specifications

As shown in the figure, the adaptation of this process for SAFESPOT consists of four interlinked stages. The activities regarding the Infrastructure and Vehicle Platforms are shown on the left. The first stage involves defining the functional areas and data flows, which are derived from the system requirements (see deliverable D1.2.3). This stage is described in this Data Fusion Specification deliverable. In particular, here the identification of the input/output parameters of the in-vehicle platform data processing activity, is provided, taking into account:

- the output of the in-vehicle systems (for vehicle dynamics, body/comfort, environmental perception, occupant safety, etc.) for the data fusion process
- the output of the data fusion process for the LDM

Based on the results of these 2 stages and the mentioned flexibility requirement of the prototype for different vehicles, configurations and applications (use cases), a physical architecture has been designed;

The task of specifying the data-fusion issues has required constant consideration of the simultaneous developments being made in the other subprojects. Their requirements and expectations have developed in a response to their own progress as they specify their own components. This deliverable provides a description of the result of this iterative, consultative development process.

1.3. Deliverable structure

This deliverable is so structured.

After this introductory chapter, the scope of data-fusion is shown, presenting the framework most used for these goals. Moreover, a brief overview of the most common methods used for object and situation refinement is illustrated, with a particular attention on how it is adapted for SAFEPROBE case. These issues are addressed in Chapter 2. Chapter 3 is dedicated to system architecture, where the more general JDL Architecture is used as starting point. In addition, also the system components are presented, with a description of the main input and output signals. Chapter 4 provide more details, with a description of the modules constituting the data-fusion framework selected for SAFEPROBE. Here, each sub-module is specified, pointing out the features of the three main DF modules: the Object Refinement, the Situation Refinement and the Co-operative Pre Data-fusion. Moreover, an overview of data acquisition and information provider components are described.

The state of the art and more details on PROFUSION2 project can be found in the Appendix A

2. Scope of Data-fusion

The main goal of the data-fusion (DF) activity is to reconstruct the traffic scenario around the vehicle thanks to the data collected from several sources of information. In particular, depending on the number of on-board sensors and on the type of data, the reconstruction will be more precise and accurate [3] than using information coming from one single sensor. This allows either improved accuracy from existing sensors or the same performance from cheaper sensors. On the other side, it can happen also that after the fusion process, estimations may be less precise (e.g. show an increased standard deviation). However, the overall *performance* (of the estimation) still increases, since the integrity / reliability of the estimation increases with more measurements. Thus, accuracy can worsen, but the fusion is done because the trust in one sensor is not always the best solution: by this viewpoint, what is improved, is the *performance* of the estimation, which still increases, since the integrity / reliability of the estimation increases with more measurements.
All in all, the data fusion algorithms have to be flexible and modular enough to be used in different kinds of vehicle using different equipment. A proposed architecture will be shown in the following chapter and it is based on the data-fusion architecture defined by PROFUSION 2.
A set of issues can be arisen, above all, about the interactions with the other SPs inside SAFESPOT (SF) with whom it is necessary to create links and synergies, in particular with SP4 and its applications. Thereby, the DF task has to fulfil the requirements – at least most of them – coming from the applications and the relative scenarios, in terms of both agreed specifications and in a common architecture definition (including protocol interface).

In this context, multi-sensors data-fusion is an emerging technology and many techniques are drawn from a wide range of areas, including artificial intelligence (AI), pattern recognition, statistical estimation and other areas. Many literature materials can be found, such as in [3] and in [6]; hereafter a brief survey of the different approaches is presented, with specific attention to object and situation refinement topics. The most traditional techniques to combine and process data regard some form of Kalman or Bayesian filters; however, in most recent years, there has been a trend toward the use of soft techniques, such as fuzzy logic (FL) and Artificial Neural Networks (ANN).

Despite the fact that there are more than 30 fusion architectures, proposed for data fusion, in order to pursue the goals of SAFEPROBE project, we have selected the so called JDL fusion architecture. This is the most widely cited model and it was created by the *American Joint Directors of Laboratories Data Fusion Subpanel* (see [7] and [8]).

2.1. JDL Fusion Architecture

The JDL model divided the data-fusion process into a series of steps (8 steps), which make up a sort of hierarchy of processing. Of course this is not the only example of a possible architecture and moreover it has a military origin, nevertheless it provides a useful structure with which it is possible to classify fusion algorithms.

Based on the JDL process, 4 main levels can be derived (see also references [3], [9], [10], [11] and [12] for more details about it). Moreover, a particular contribution is given by [13] and with reference to this paper, the following considerations can be done:

- Levels 0 and 1 depend only on data generated within the vehicle
- Level 2 is the one where:
    - o the digital road map information are used and the data from vehicles are included
    - o data from the neighbouring vehicles is inserted, together with their position and speeds
- Data Fusion is partitioned for all levels in an association and estimation process.
- Output of the fusion levels should increase in the level of understanding i.e. from signals to a spatio-temporal situation

The general scheme is the following:

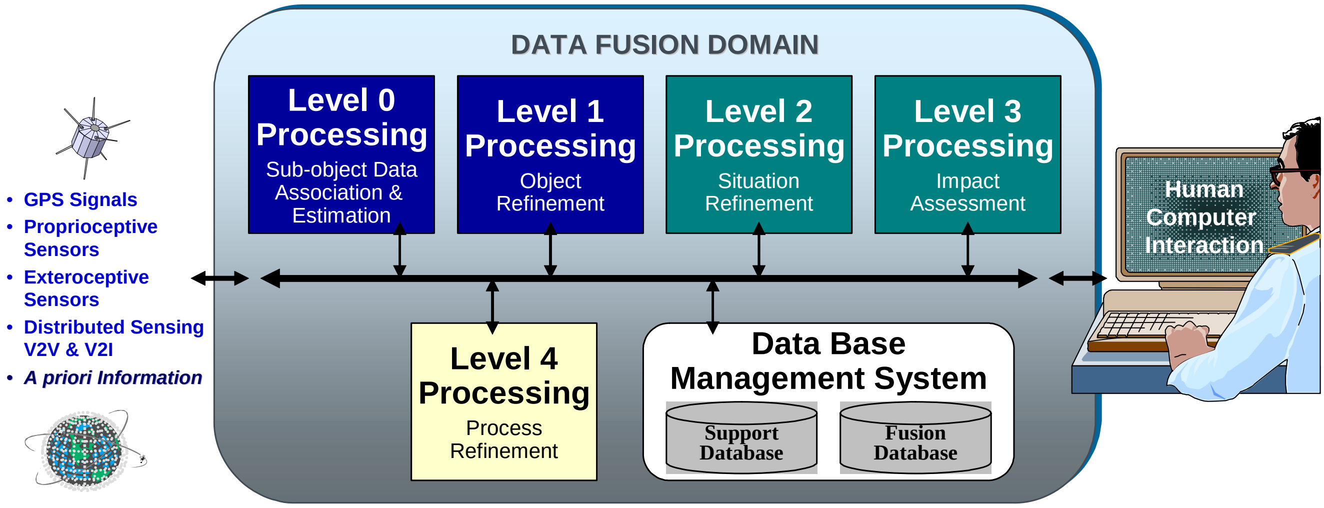


Figure 2: JDL DF functional model

Considering the aforementioned Data Fusion Levels, it is possible to say that (c.f. [13] for further details):

- **Level 0 – "Sub-object Data Association & Estimation"** = it is the features-signals level, namely pixel intensities, range readings, encoder readings, steering wheel angle and so on
- **Level 1 – "Object Refinement"** = it deals with entities, that is location, track, identity, activity state, etc.
- **Level 2 – "Situation Refinement"** = it is the entity situation, namely the relationship of the entity with other entities, an aggregation of information, the association of the subject vehicle with the map/map matching
- **Level 3 – "Impact Assessment"** = it deals with the evaluation of the entity situation with respect to the subject vehicle (threat assessment), it is the understanding of the situation.

- **Level 4 – “Process Refinement”** = it looks into the effectiveness of the information inferred, configures the system so as to enhance output of the different levels. Enhances the level of confidence

In particular for our goals, we focus on the object and situation refinement, as described in the following paragraphs.

2.2. Object Refinement

Based on what is stated in the previous paragraphs, the object refinement (OR) is regarded as level 1 of the JDL architecture. OR is defined as the process combining location, parametric and identity information, in order to achieve reliable representation of individual objects; in particular, for SAFEPROBE case OR is intended to illustrate and emphasize the need to **keep some history** of the data for:

- timely alignment of measurements to a common cycle
- associate measurements from different sources of information and confirm objects (even before they can be put into LDM)
- remove false objects (false positives)
- estimate the objects’ position uncertainty
- assign to each object their own features (see the dedicated chapter on input/outputs of the DF modules)

The processing of historic data for state and state uncertainty estimation, especially when performed recursively, is usually called *tracking* and (Extended) Kalman filtering is just a special, although often applied, form of tracking

In details, OR is usually partitioned in 4 parts:

1. data collection/registration;
2. data association;
3. position attribute estimation;
4. identification.

Point 1) regards the data collection and possibly registration into a common frame of reference; data association (point 2) attempts to collect data originating from the same object into a single track; points 3) is focused mainly on computing the target’s state; eventually, identification step (point 4) has the aim to classify the object that the measurements originate from.

2.3. Situation Refinement

Situation Refinement is also known as situation awareness or situation assessment. It can be understood as the knowledge of what occurs around the ego-vehicle. Although the general idea of situation refinement is well known there is no agreed definition. Humans are regarded as the only entities with the ability of situation awareness.

In the following, a definition of situation refinement proper for SAFESPOT is reported (see [48]): situation refinement represents the estimation of relationships between entities in road environments that maybe are of the same type or different types. It provides an intermediate additional higher level of input to applications and its final aim is to make a decision out of a set of predefined situations accompanied with a confidence value.
According to JDL Architecture situation refinement level is one of the most important levels in this architecture. It is responsible for identifying the relationships between the elements of the road environment (ego vehicle, detected objects, lanes etc.).
Situation refinement includes the determination of the performed manoeuvre not only of the ego vehicle but also of the detected objects in the road environment, the identification of the moving objects and the classification of their position in respect with the projected position of the ego vehicle in the future and finally the determination of the driver intention (without using any driver models) [49].
Due to the limited knowledge of the actual behaviour and the uncertainty introduced by the sensors, the use of evidence theory is necessary in order to establish the situation refinement algorithms.
Within the situation refinement module both Kalman filtering and Dempster-Shafer reasoning will be used. For example in “Lateral Dynamics Estimation” module we use Kalman Filtering; in “Manoeuvre Detection” and “Driver Intention” modules, Dempster-Shafer reasoning will be used.

2.4. The SAFEPROBE case

Many influences have affected the development of DF algorithms inside SAFEPROBE sub-project; in particular, the results of the EU project PROFUSION2, a summary of which is found in Appendix A.

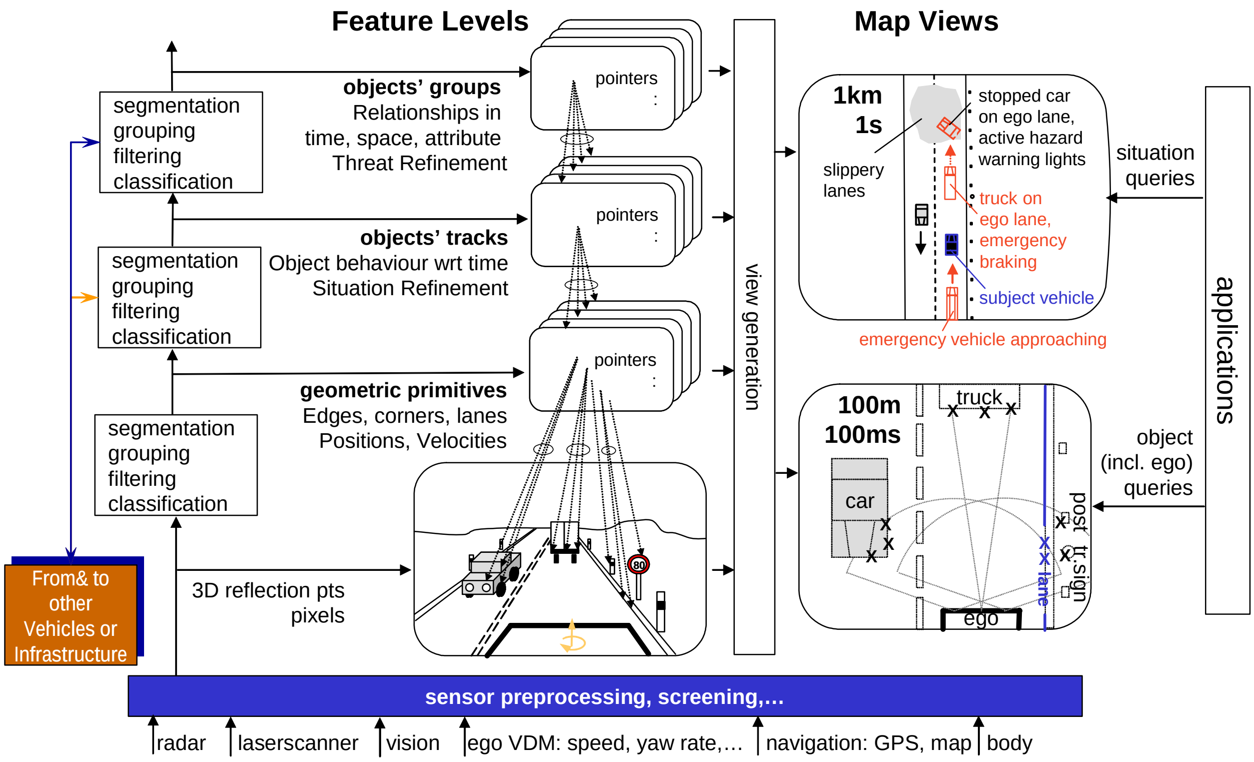


Figure 3: Hierarchical architecture for SAFEPROBE, after the 4D/RCS architecture [50]

Within the realm of autonomous ground vehicles R&D, together with endeavours in the robotics and artificial intelligence communities; and through the sponsorship of the National Institute of Standards and Technology (NIST) in the USA, the 4D/RCS (4 Dimensional/Real-Time Control System) architecture has been developed and is currently in use. It provides a framework for the design of sensor-based autonomous vehicles and the representation of information that endows a situational awareness understanding of the vehicle surroundings in a machine understandable manner [50]. The 4D/RCS architecture has been largely adopted by several research groups and in some cases aligned with the JDL Data Fusion Model as it provides a layered structure for the representation of information with various levels of granularity and information and for different functions associated to the target vehicle.
Figure 3 shows a modified representation of this architecture as applied to co-operative vehicles, with emphasis on the level of refinement necessary as well in the feature level together with the extend that each layer should cover. This is an example on the manner in which a multi-resolution and multi-level approach can be represented in order to illustrate in a hierarchical way a representation of the world and it is chosen for SAFESPOT case.

3. System Architecture

In this chapter, the general system architecture and a description of each sub-module, including the INPUT / OUTPUT parameters, are presented.

3.1. Overall System Architecture

With reference to SP7 core architecture (Guyancourt diagram) and to what is described in [47], the architectural scheme of SP1 platform is presented in Appendix B.

In particular, the aim of this document is to investigate more deeply inside the “yellow” module, named “*Data Processing Fusion*’.

3.2. Data-fusion Architecture

The general DF architecture is represented in Appendix C, showing the functional component diagram architecture in details:

The details for DF topics are described in chapter 4:

- Paragraphs 4.1 and 4.2, in which also the Co-operative Pre-data Fusion module is illustrated
- Paragraph 4.3 is about the Situation Refinement
- Paragraph 4.4 cope with Information Provider module
- Paragraph 4.5 presents, eventually, the Data Acquisition module

Before it, hereafter some general issues about SF-SP1 platform are presented. However, for a specific view on HW and SW architecture, see deliverable D1.2.3 (reference [52]).

Firstly, there is the sensorial system, which is constituted in our case by the following devices:

- **Positioning Data** ⇒ data coming from positioning module (by SP3)
- **In-vehicle Data** ⇒ data available in the ego-vehicle CAN bus; at the moment, the following data are regarded as necessary:
    - Yaw-rate
    - Speed
    - Steering angle
    - …
- **VANET Input** ⇒ these data represent the communication ones
- **Perception Sensor Data** ⇒ at the moment they regard the long-range Radar; possibly, some others coming from camera detection will be added

- **Laserscanner** ⇒ these data come from Laser-scanner sensor and go into the CDPF module, for a dedicated processing phase.

After that, the "**Data Acquisition**" module has the aim to collect data coming from ETHERNET-SF dedicated bus and compute them in an appropriate way (i.e. transforming the data from Geodetic reference system to Cartesian one).

Then, there are the two fundamental modules for data-fusion process: "**Object Refinement**" (OR) and "**Situation Refinement**" (SR). Both will be described in detail in the following paragraphs.

The OR module is made of several sub-modules, the main ones are:

- Co-operative Pre-Data-fusion (for a preliminary fusion of data from the Laser-scanner and the VANET)
- Sensor Level Fusion for other on-board Sensors except the laser scanner (for the synchronization of data by a temporal and spatial viewpoint)
- Central Level Fusion (for the "complete" fusion process)

The main sub-modules for the SR, are:

- Ego-Vehicle (future path, manoeuvre detection etc. concerning the ego vehicle)
- Object (manoeuvre detection, lane assignment etc. concerning other vehicles in the road environment)

Eventually, the results from the OR and SR modules are to be imported onto the LDM data base, this will be implemented by the "Information Provider" module according to the interfaces specified in the LDM task of the SP3.

3.3. Data-Fusion General Description

In this paragraph, the main IN / OUT variables are described:

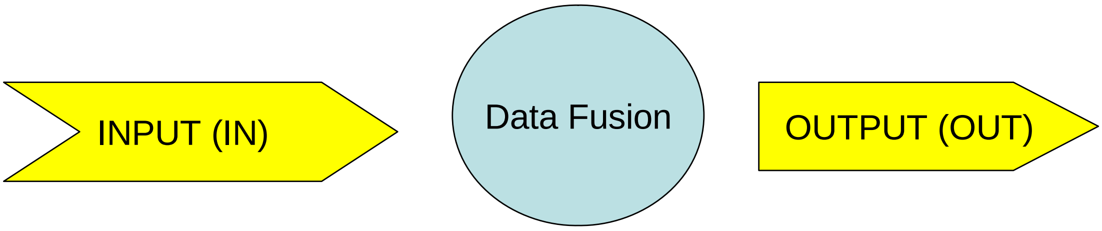


Figure 4: IN/OUT scheme for data-fusion

3.3.1. Input Variables

They are listed in the following table:

Source	Variable
Laser-scanner (after dedicated processing phase in CPDF module)	Obstacle data
	Raw data

Long-range Radar (LRR)	Obstacle data
	Sensor data
VANET	V2V communication
	V2I communication
	Static and dynamic information
Camera + Image Processing (IP)	Road boarder
	Lane detection
	Road curvature
	Obstacle data
Ego-positioning	Relative position of vehicle
	Absolute position of vehicle
Host-vehicle CAN bus (LDM)	Ego-vehicle data

Table 1: input signals for data-fusion

Here only a summary is presented; more details about input signals are reported in the deliverable D 1.3.1.

These are the main data requested; the details for each sub-module constituting the DF will be described in chapter 4.

3.3.2. Output Variables

The main outputs are the sum of the output variables coming out from each module:

Source Module	**Variable**
Situational Refinement	Data structure: • Object(i) • Manoeuvre(x) • Probability(p)
Co-operative Pre-Data-fusion	Position of tracked object(s)
	Relative/absolute velocity of tracked object(s)
	Object classification
	Object size
	Confidence
Object Refinement	Object features: • Distance • Velocity

	• Angular position

Table 2: output signals from data-fusion

The data comes to the module called “Data Information Provider”, which has the aim to write data in the Local Dynamic Maps (LDM).

4. Description of Data-fusion Modules

Based on what is stated in the previous paragraphs and in the different types of architecture, a description on ORM, SRM, CPDF, as well as finally an overview on the Information Provider Module (IPM) and Data Acquisition Module (DAM) will be provided in this chapter.

4.1. Object Refinement Module Description

With reference to the scheme in paragraph 3.2, this section points out the main topics about the Object Refinement module. In particular and for the sake of simplicity, hereafter a general overview of this module is reported in Appendix D.

It is constituted by three main points:

1. Sensor-level Fusion for On-board Sensors
2. Central-level Fusion
3. Co-operative Pre Data-Fusion (CPDF)

4.1.1. The Activity Diagram for ORM

With reference to UML framework, chosen by the project to carry out the requirement and specification phase, in this section the Activity Diagram for ORM is presented. An **activity diagram** describes the workflow behaviour of a system and under this point of view it is similar to state diagrams[2] because activities are the state of doing something[3]. The activity diagram for ORM is reported in Appendix E.

At the beginning, there is the “Initial Activity” point; then, data are collected and acquired. After this phase, the data are aligned both in time and space, putting them into a common reference coordinate system (RCS) and on the same temporal basis. The further step is the tracking phase, which is done for data coming from Radar sensor and VANET. After this process, together with data coming from CPDF module (see next paragraph 4.2 for more details), they enter into the Data Association module, whose aim is to associate data and to understand if there are more objects or same object “is seen” from different sensor. Of course, depending on the actual data, diverse strategies can be adopted to estimate the uncertainty level, computed in the following module; in fact, if there are inputs only from VANET, for example, the

[2] A State diagram shows the different states an object is in during the lifecycle of its existence in the system, and the transitions in the states of the objects. These transitions depict the activities causing these transitions, shown by arrows.. An Activity diagram talks more about these transitions and activities causing the changes in the object states.

[3] The Activity Diagram describes the state of activities by showing the sequence of activities performed, which can be conditional or parallel, In other words, the Activity Diagram is a dynamic diagram that shows the activity and the event that causes the object to be in the particular state.

confidence level is expected to be quite low. After the process to decide if a "fused object" has to be maintained or deleted, the list is given to both the SRM and the Local Dynamic Map (LDM), so that the obstacles data can be write on and to be available for applications (especially from SP4).

Now, next paragraphs describe in detail the other sub-modules constituting the OR module. Finally, the last section describes the class diagram for this module.

4.1.2. Sensor-level Fusion for On-board Sensors

The Sensor-level Fusion for On-board Sensors (SFOS) is shown in Appendix F.

The module receives information from external environment, as they are transmitted by GATEWAY (see [47] for more details) which has the aim to convert data to ETHERNET protocol (from other protocols, like CAN or RS232, etc.) and to assign a time-stamp to each one.

In output, all data regarding objects and host-vehicle are provided, after tracking and alignment.

SFOS is composed by two main parts or components:

- Time and Spatial Alignment (TSA)
- Tracking and Classification (TC)

These are described as follows.

Time and Spatial Alignment

The goal of this sub-module is to perform the alignment of data by a common spatial and time reference frame.

In particular, the spatial alignment implies the procedure to align all data in a common spatial reference system and it is carried out by a double transformation of coordinates: from Radar sensor to Vehicle reference coordinate system and from absolute GPS coordinate transformation to vehicle reference coordinate system.

About the time reference, this implies the procedure to align all data in a common reference time. The first step of a data combination process consists in the synchronisation of information provided by different sensors. An example of what is meant, is depicted in the following figure (for more details, see [55]):

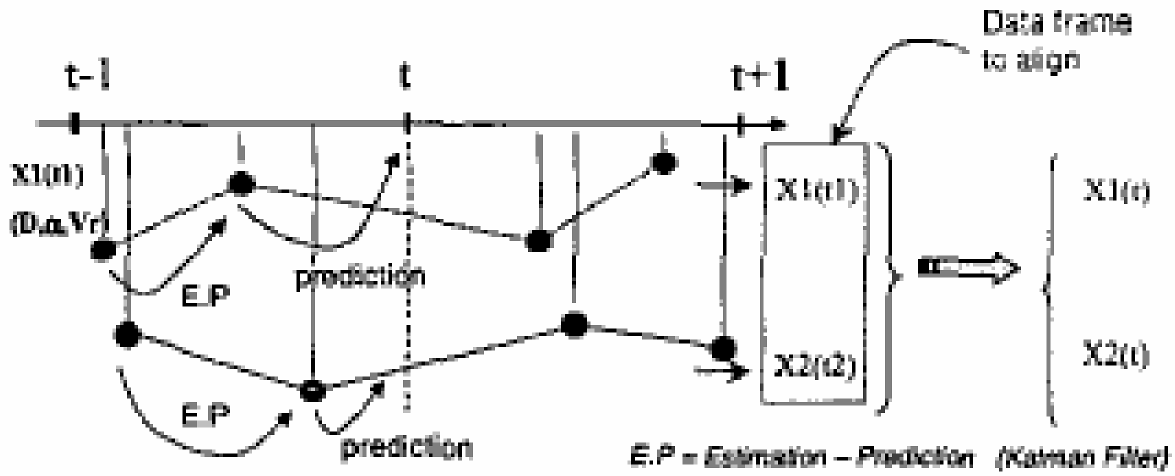


Figure 5: example of temporal alignment process, as described in [55]

This temporal alignment is based on Kalman filter algorithms, based on a succession of estimation – prediction cycles and therefore the results of coming from "Tracking and Classification" are used to do this job. The time base on which the data are rescaled either independent on sensors (and thus on an artificial base) or aligned on a specific sensor time base. In the SAFESPOT case, it is adopted the second choice and the GPS time is considered. Then, the computation cycle will be based (if possible, depending on the performances) on the refresh time of Long-range Radar (LRR) sensor, that is of 100ms. As suggested in [55], this global temporal scale can be referred the *fusion-time scale* and so all data are fused at this (same) time t. Of course, a rescaling in time implies a rescaling in space as well and this is taken into account in the algorithms.

The situation is:

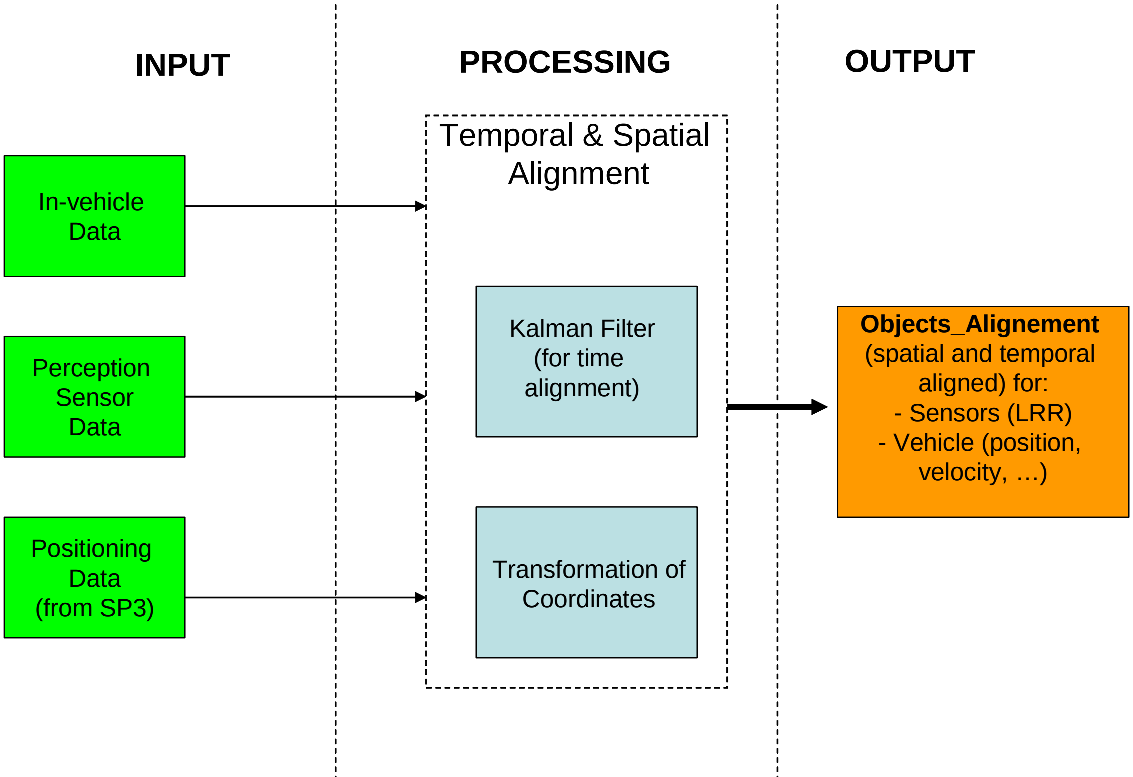


Figure 6: Details for TSA components

The main inputs are:

- In-vehicle data (Position, Velocity and Yaw-rate)
- Perception Sensor Data (from LRR, at the moment)
- Positioning Data (from SP3, related to vehicle data)

The outputs consist in a number of *N* objects (each one with *M* associated parameters, which characterise them) aligned in terms of time and space. The M parameters are:

- x-, y- position
- x-, y- components of velocity

Some other features can be added, if needed.

Tracking and Classification

The goal of this module (TC) is to perform the tracking of objects after their spatial and temporal alignment. Actually speaking, this sub-module is very connected to the previous one, since in order to obtain an efficient temporal alignment (see also [55]), a tracking process is necessary. So, in a certain sense, these two objectives are performed together. Nevertheless, the situation is depicted below:

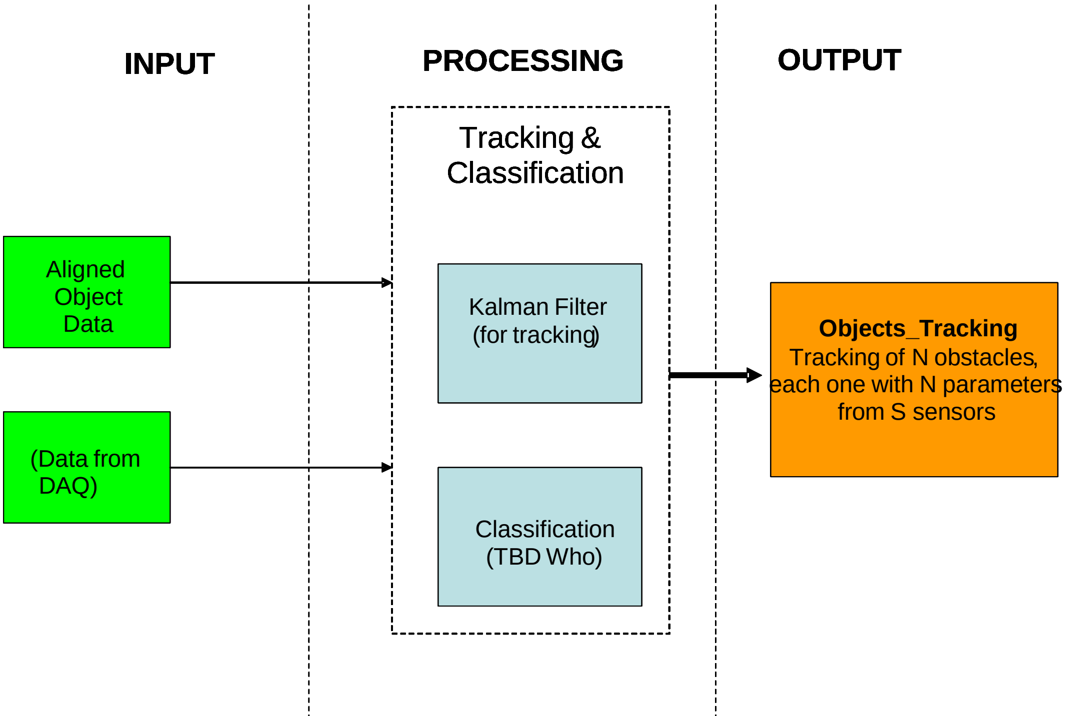


Figure 7: details for TC component

The INs are the data from the TSA module and optionally some further information coming directly from the gateway.

The OUTs are a list of *N* tracked objects (aligned in space and time), each one with *M* parameters, from *S* sensors. The M parameters are the same listed before.

4.1.3. Central-level Fusion

The component diagram for the Central-level Fusion (CL) is illustrated in Appendix G.

The CF sub-module receives in inputs data from SFOS and CPDF modules (if necessary, from Gateway too) and then it gives as main output the list of fused obstacles.

CF is composed by:

- Data Association (DA)
- Uncertainty estimation (UE)
- Object Maintenance (/ Deletion) (OM(D))

These modules will be described as following.

Data Association

DA module has the aim to associate objects whose data coming from different source of information, or even better, to associate the different tracking as provided by the previous module (SFOS). In other words, the goal is to understand if one object is seen from several sensors, or there are diverse objects (maybe at different angular field of view). In this context, at the moment these sources of information are taken into account:

- Radar
- VANET
- CPDF (Laser-scanner data processing)

The situation is presented below:

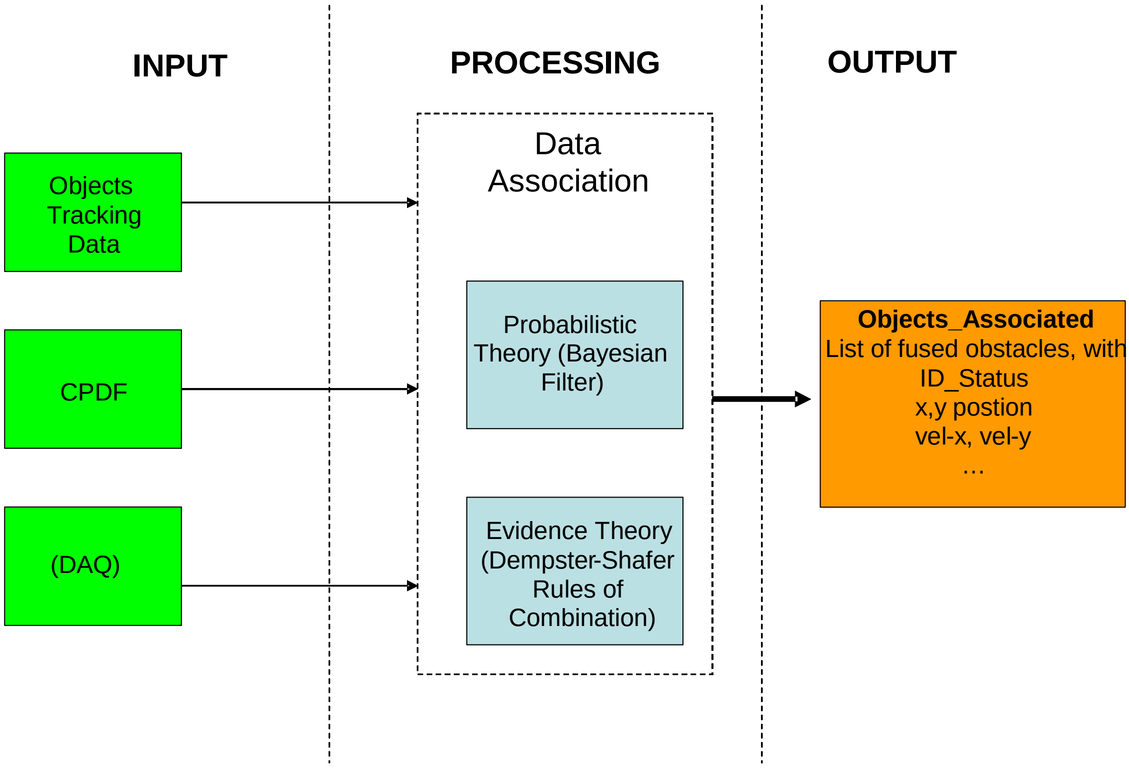


Figure 8: details for DA component

As pointed out in the figure, the inputs are tracking data from previous module, the outputs of CPDF about objects and possibly some further information from Gateway.

The outputs consist in a list of fused objects, that comprehends:

- ID_Fused_Status ⇒ F = objects fused; R = objects from Radar; V = objects from VANET; C = objects from CPDF module
- X-position;
- Y-position;
- X-component of speed;
- Y-component of speed

The algorithms used to combine inputs and obtain such kinds of data can be based on Probabilistic Theory or Evidence Theory; at the moment the choice is still under discussion, but further details on that will be written down in a dedicated document.

Uncertainty Estimation

The aim of this module is to assign an accuracy value to the parameters defined up to now, namely to estimate the uncertainty affecting the computed parameters. The situation is shown as following:

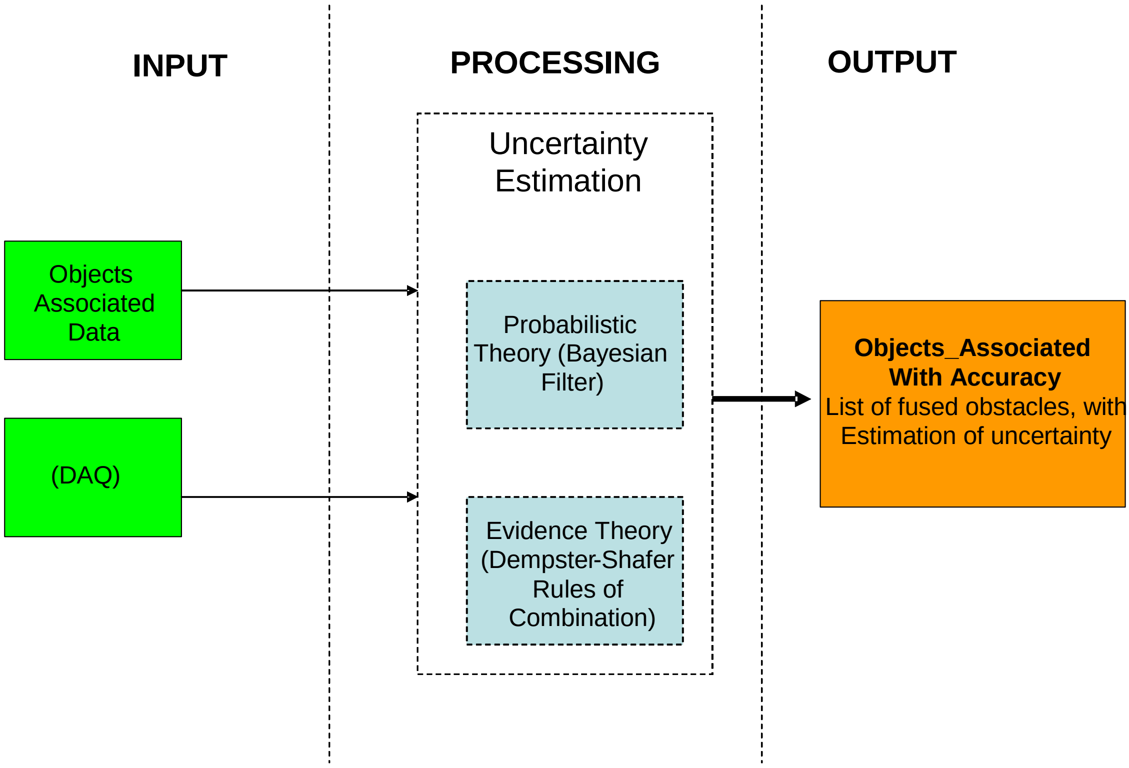


Figure 9: details for UE component

The inputs are the data coming from the previous module, while the main output is the list of fused objects (as defined from DA module), with an associated estimation of uncertainty.

About the algorithms, it is valid what claimed before: Probabilistic Theory or Evidence Theory will be used to assign an uncertainty value.

Object Maintenance

The main goal of OM is to maintain or delete an object, namely assessing if it is a new one, or an old object already tracked in the previous moments. The situation is:

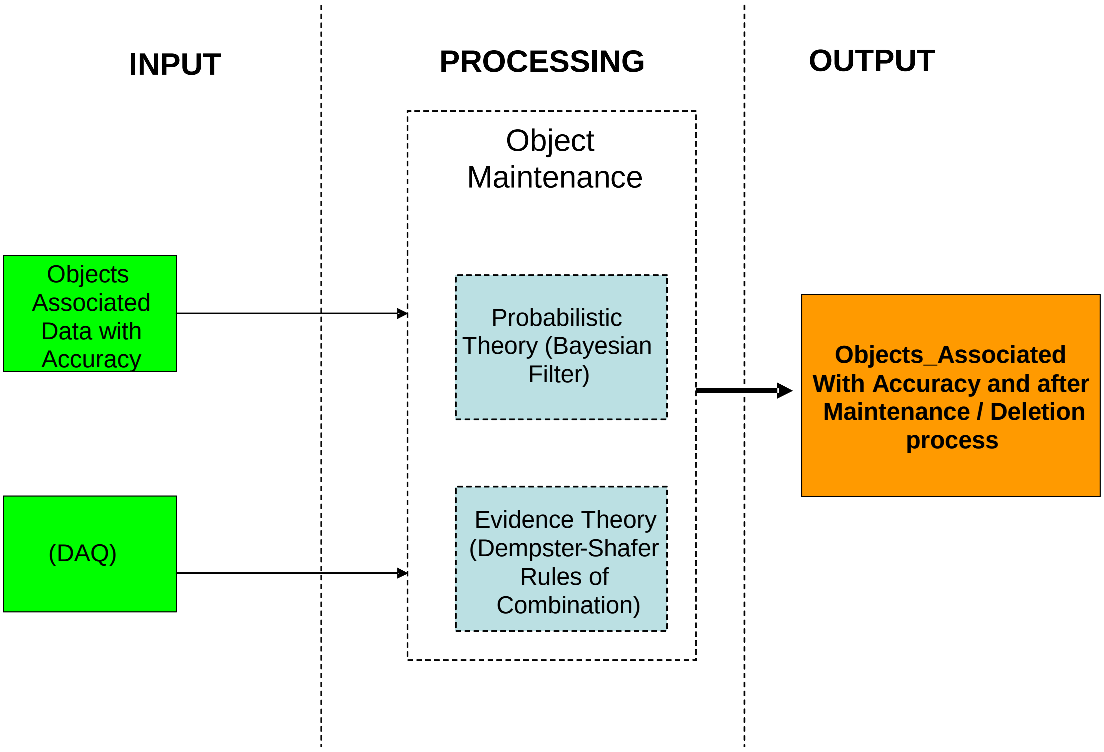


Figure 10: details for OM components

Its INs are represented by the object data with accuracy, as defined by the previous sub-module. The OUTs consist in a decision process, to state if an obstacle has to be deleted or is kept, because it has to continue to be tracked. How to achieve this, is still under discussion at the moment, but further details on that will be written down in a dedicated document.

4.2. Co-operative Pre-data-fusion Module Description

The Cooperative Pre-Data Fusion (CPDF) is an environment perception sub-system, providing information about objects in the host-vehicle's vicinity to the main SAFEPROBE data fusion system in particular to the central level fusion. A schematic of the overall module architecture for the Cooperative Pre-Data Fusion is shown in Figure 18.

4.2.1. Algorithms Description

The Cooperative Pre-Data Fusion makes use of four data sources feeding into different levels of the pre-data fusion process. The first source is the Laser-scanner, which gathers a range profile of the environment. Figure 11 shows an example environment scene of an intersection. This captured raw data is sent to the scan data pre-processing and segmentation sub-module of the CPDF (see figure 18 for a rage profile).

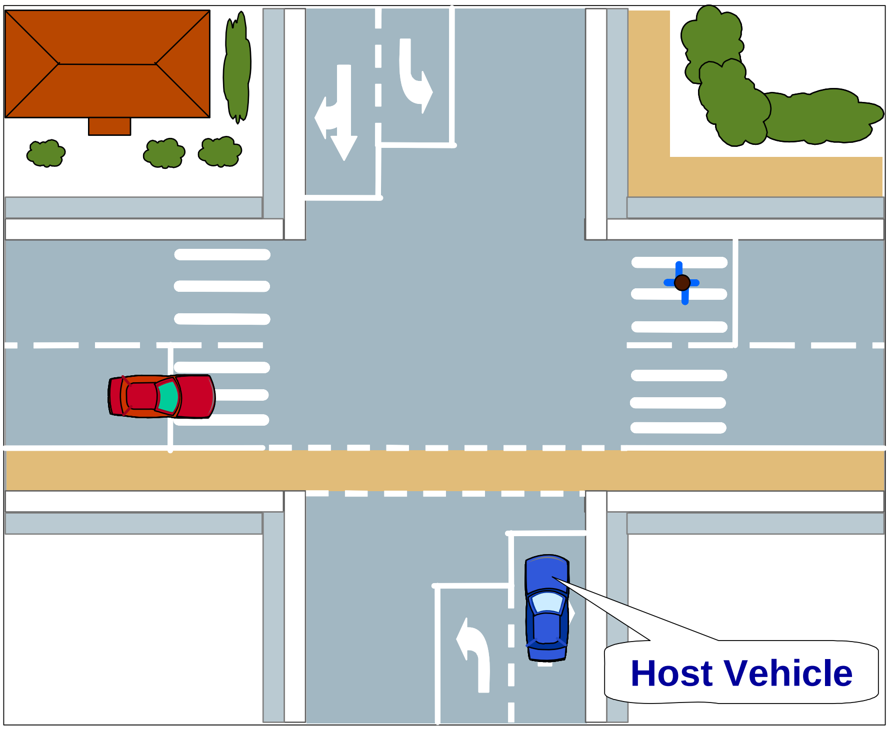


Figure 11: Example scene

In the subsequent step, information on the surrounding static road and lane geometry is taken from the static map, is put on top of the range profile (see Figure 13b). Based on this overlaid map information, the module distinguishes between scan data, representing background objects and scan data at foreground objects like road users. Following this differentiation scan data outside the ROI (region of interest) is not processed in the following. Due to the so called **background elimination,** depicted in Figure 13c, the overall processing performance and robustness increases significantly.

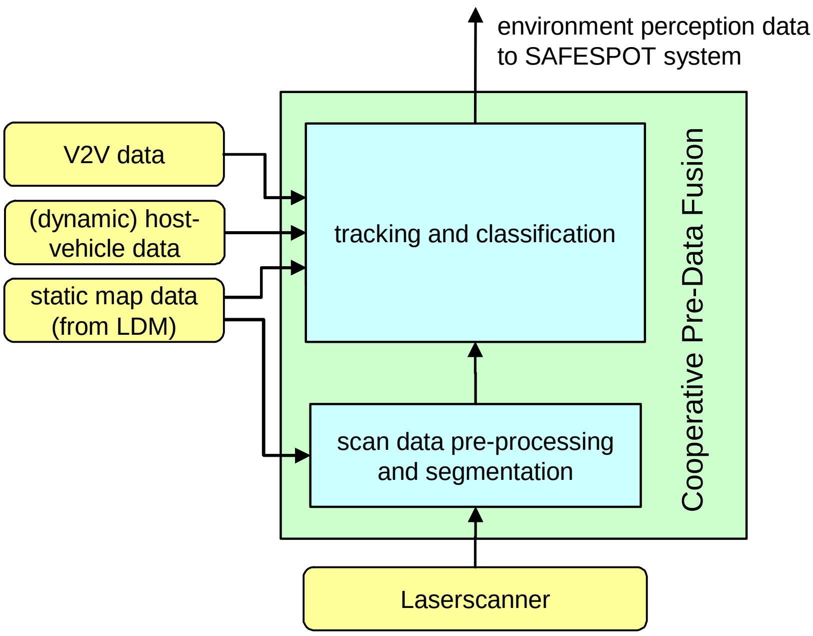


Figure 12: Schema of the Cooperative Pre-Data Fusion process

The subsequently performed segmentation clusters single scan points into groups, each representing one real object. These segments are then forwarded to the tracking and classification module.

The tracking of established objects is performed by comparing the segment parameters of a scan with predicted parameters of known objects from the previous scan(s). Unrecognised segments are instantiated as new objects, initialised with default dynamic parameters.

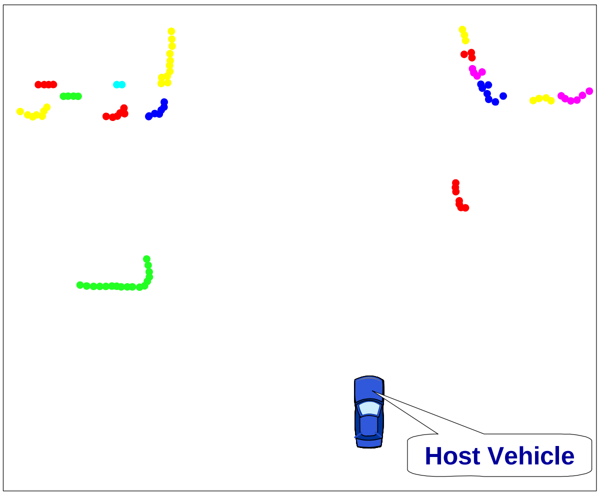
The object's state parameters are then estimated by a filter which allows complex dynamic models, required for precise object tracking. An additional improvement of the tracking performance and reliability is achieved by the cooperative fusion with static and dynamic vehicle information transferred via V2V into the filter.

Road users are classified by their typical angular outline using only the geometric data. Additionally, the object's history and its dynamic data are necessary to enable a robust classification, which is currently the state of the art. A further optimization is achieved by adapting the probability for an object class based on its position within the static map. On top of this, V2V data providing the vehicle's class is fused into the classification process with a high probability value.

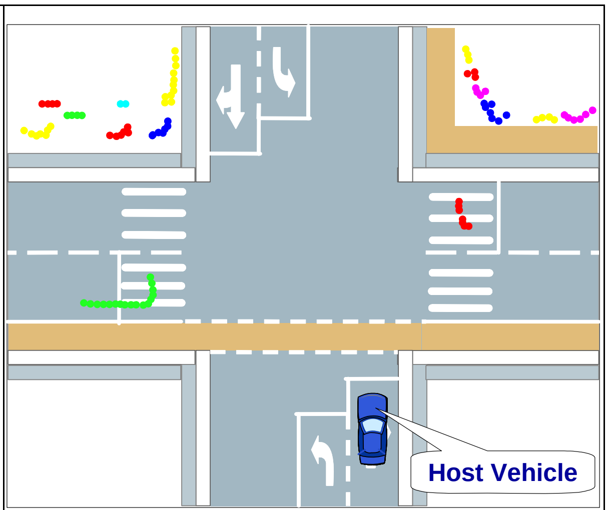
The gathered object information data is then sent by the Cooperative Pre-Data Fusion module to the central level fusion module, which fuses and processes the object information collected by all installed environment perception systems.

4.2.2. V2V Data Association

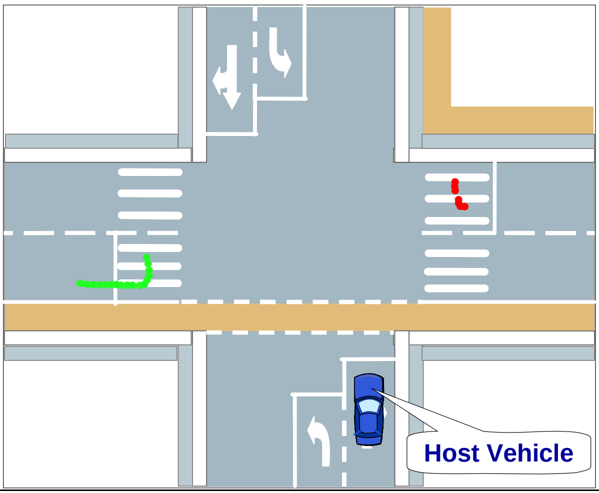
One major challenge within this cooperative approach described above is an accurate and robust association of V2V-data to the proper vehicle detected by the Laser-scanner. In the worst case, the vehicle's position based on GPS only, is transferred from the transmitting vehicle (depicted in red within figure 19d) to the host-vehicle. This would result in a poor position accuracy and therefore cause a large search area for association process.



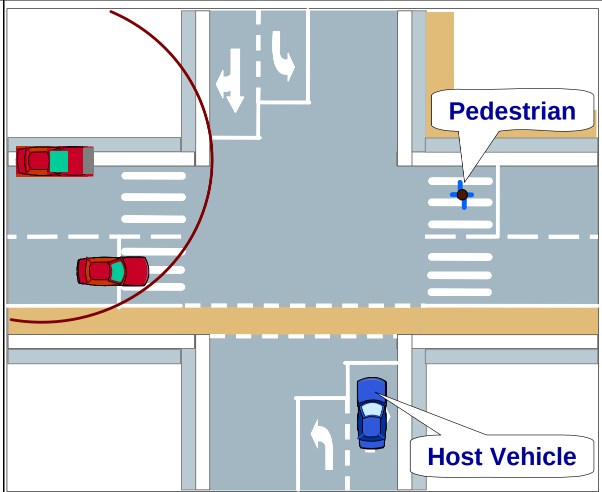
a) Laserscanner range profile (raw data)



b) range profile with static map overlay



c) background elimination process



d) V2V data association and classification

Figure 13: Cooperative Pre-Data Fusion Algorithm graphically depicted

An example is given in Figure 13d, where the light red vehicle indicates the GPS position and the red circle describing the corresponding accuracy (association area) provided via V2V. The dark red vehicle represents the vehicle's position measured by the Laserscanner system. For the depicted case, the association is straight forward while more complex situations, with multiple vehicles (detected by the Laserscanner) within the vicinity of the V2V-position, require a more sophisticated approach. This challenge is tackled by calculating an association likelihood for each detected vehicle using information such as position, driving direction, vehicle speed etc.

4.3. Situation Refinement Module Description

A high level description of the situation refinement module including the inputs and outputs to it is reported in Appendix H. This description is called “high level” because the details, about how the sub-modules inside the main SR module interact and how they are connected to the input and the output, are hidden.

The situation refinement module consists of two main modules (ego vehicle and objects) which further include several sub-modules. More details on this topic can be found in the deliverable D 1.3.1.

4.4. Overview of Information Provider Module

Information Provider (IP) module has the goal to take all the results coming from data acquisition (e.g. ego vehicle state), object refinement (e.g. other vehicles states) and situation refinement (e.g. ego and other vehicles manoeuvres) and cast them into transactions for the LDM. This component includes the maintenance of the LDM, such as removal of decayed dynamic objects. For more details, see deliverable [47].

4.5. Overview of Data Acquisition Module

While the information provider module delivers the results of the data fusion platform, the data acquisition module (DAM) prepares information as inputs for the data fusion, as well as for direct flow into LDM.
As defined by the DF-architecture in §3.2, the data acquisition module collects data measured in ego vehicle (CAN) or by additional sensors, received from satellite (Positioning) and road side infrastructure or other vehicles (VANET). Also the data from local dynamic map (LDM) flows into DF platform via DAM.
The DAM has to prepare a wide range of data of different natures. Also the DF modules have different requirements on input data. Therefore, the main task of the DAM is to harmonize the different information sources and provide the data to the DF platform in a systematic and effective way.

5. Summary and Conclusion

This deliverable has illustrated the main data-fusion topics, developed inside the SAFEPROBE project of the IP-SAFESPOT. The focus has been on the description of the methodology, ideas and rationale, used to select the approach and algorithms that are to be implemented in the SAFESPOT systems. A thorough description is included of the selected general framework and fusion architecture. It is based on the JDL model for data fusion, with emphasis on two levels: object and situation refinement. These correspond to the two main modules in the data-fusion platform.
Moreover, it has been also described the fusion architecture. The implementation of this fusion framework is defined in an specific deliverable, namely D1.3.2: “Hardware and Software Platform Specifications”; [47].
The structure of input and output data has been defined for more detail see D. 1.3.1. There is a description of the messages needed by every module, their type, value range with unit of measure, as well as the relative resolution and accuracy. The specifications of the input and output signals are the basis for the definition of the data structure, on which a dedicated activity is in progress at the moment.

Due to the high complexity in the implementation and definition of the SP1 platform, including the data-fusion part, not all the work has been completed. Some activities remain open in particular with regard to the implementation of the experimental phase and the tuning of parameters in optimal manner. This will be the focus of activity within the coming months. Further details will be included in the deliverable D1.4.3 “Algorithms and SW Prototypes”, where all the open points, and a more precise and thorough description of the used algorithms will be provided. The details of the SW implementation will be specified in the referred deliverable.

This deliverable, together the one addressing HW and SW specifications form the basis for the definition of the whole SP1-platform and for the choice of the structure and components that are to be included in the demonstrator prototypes. This includes details of the demonstrator vehicles and components such as sensors, computers, etc. That is, it describes the details of what is to be implemented as part of SP1.

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7. Appendix A – A Brief State of the art: the case of PROFUSION2

In this paragraph, an introduction is presented, about how this item is investigated in PF2. The reference materials are thereby [4] and [5] (for more details, see also web-site).

The sensor data fusion (SDF) development inside PReVENT and the SDF research in the automotive field is significantly influenced by ProFusion2 (PF2). The Preventive and Active Safety Applications project (*PReVENT*), contributes to the safety goals of the European Commission (*EC*). The majority of these functions are characterized by using perception strategies based on multi sensor platforms and multi sensor data fusion. *ProFusion2* has the responsibility to streamline the multi sensor data fusion in the functional field activities. Thereby, a major objective of *ProFusion2* is to improve the perception as a whole by developing sensor data fusion approaches and to implement and integrate these approaches into demonstrator cars. Another important objective is to research in the field of sensor data fusion in order to identify high potential concepts. This deliverable describes the concepts related to sensor data fusion and used by one or several approaches. It also reports first results for each approach on the respective demonstrator cars:

In order to achieve these goals, five SDF concepts, which cover a wide area in the SDF research field, have been selected to be investigated in PF2 to solve a spectrum of different tasks, like e.g. the whole SDF for one application, deriving confidence measures etc. These are:

- *EARLY FUSION*
- *MULTI-LEVEL FUSION*
- *TRACK LEVEL FUSION AND SITUATION REFINEMENT*
- *GRID BASED FUSION*
- *FUSION FEEDBACK*

Hereafter, they are described with more details.

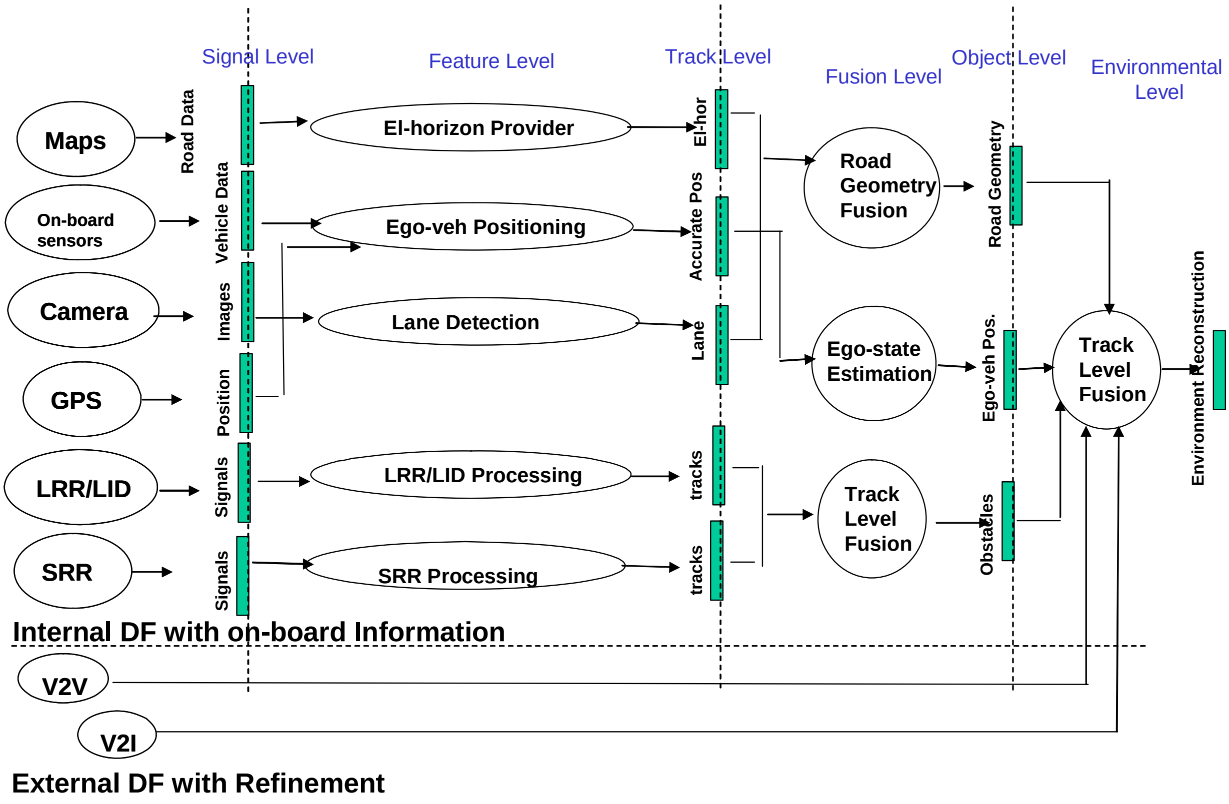
The main disadvantage of present-day sensor data fusion concepts basically arise from the lack of making (enough) use of redundant sensor information. Having this in mind the fusion methodology subsequently referred to as *EARLY FUSION* aims at remedying these specific deficiencies by taking advantage of the synergetic effects of redundant multi sensor perception on a lower level in combination with a single, sufficiently rich and complete model of the observable environment during the perception instantiation process. In doing so this approach combines pieces of information already on a sooner level compared to state-of-the-art track-based fusion systems. The aim of this method is to interpret unbiased feature input data from different sensors as a whole, using modeled entities of the vehicle's surrounding and to explain all available sensor data with help of these models. Within ProFusion2 FORWISS follows up the research and development activities regarding this methodology including an extended sensor set, confidence measures, performance evaluation methods, etc.

ICCS research and development in ProFusion2 include the *TRACK-LEVEL FUSION* approach for the object refinement and the situation refinement modules. Track-level fusion within the object refinement layer is a distributed approach that assumes one level of processing (e.g. tracking) is carried out inside each individual sensor or sensor system, and the output (track arrays) feed the track level fusion algorithm. This report includes first results of sensor level tracking, data association and track-level fusion. Situation analysis is also included which consists of two main steps: The first step is the development of the appropriate level of domain specific knowledge for the road elements, like e.g. road borders, lanes and obstacles, and the second step is the development of the decision process that is able to codify and manipulate the knowledge derived in the first step. The situation refinement work contains the design of a set of *Dempster-Shafer* (D-S) theory based reasoning systems for: Manoeuvre Type Identification, Level of Manoeuvring, Driver Intention Prediction and Lane Assignment for fused objects.

INRIA is developing an approach for multi sensor data fusion based on Occupancy Grid framework (*GRID-BASED FUSION*). The key idea is to map the environment surrounding of a vehicle using an occupancy grid and to perform perception in this occupancy grid. This occupancy grid is a regular discretization of the environment in cells, where each cell contains the probability that the corresponding part of the environment is occupied by an obstacle or not. The grid is built using all the data available at a given time. In a second step the objects currently present in the environment are extracted from the grid and tracked over time. In this deliverable, INRIA describes its first results to map the local environment of a vehicle with an occupancy grid using a laser scanner. And how to discriminate moving objects from static objects inside this grid. First results related to multi-objects tracking are also covered in this reported.

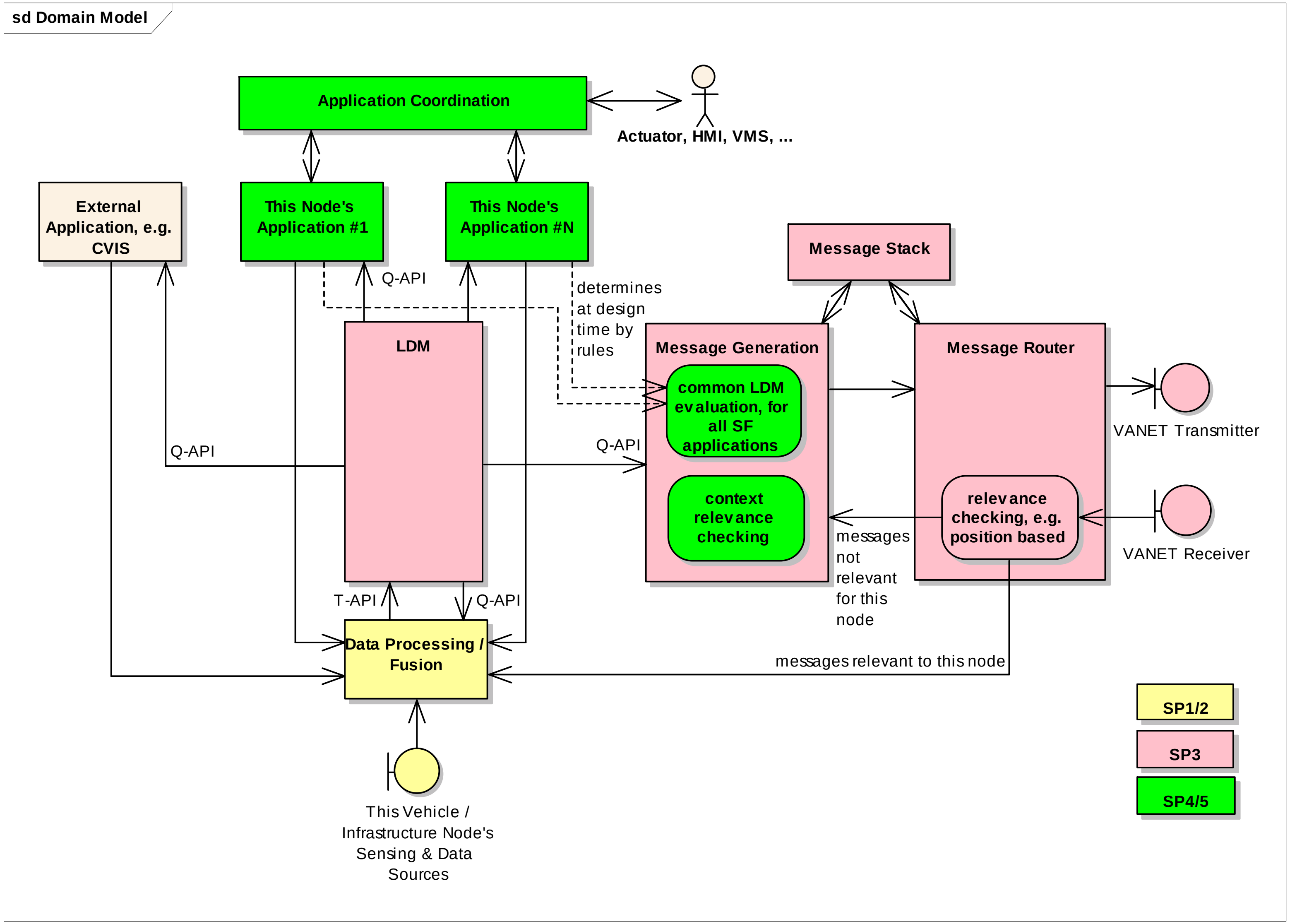
The TUC strategy is based on the *MULTI-LEVEL FUSION* approach to fuse data of multiple sensors on multiple levels of abstraction. In particular this covers the sensor data level up to the situation level. By implementing this fusion approach we are able to combine models and intermediate processing results at several levels and to use high-level to low-level and/or vice versa signal flow directions.

Back loops in the data processing are introduced by evaluating confidence measures of intermediate and final processing results to increase the degree of certainty about a specific result (confidence). A combination of fuzzy membership functions and elements of the evidence theory is used to achieve this aim.
The processing of laser scanner and radar data is done using a grid structure while radar and image data are fused with distinctive image processing algorithms in combination with the above mentioned confidence measures. The introduction of a unified and common data structure to store structural and procedural knowledge allows us to combine model and sensor knowledge, like “which object can be detected by which sensor” and “how can this object be detected”.
In addition to the above mentioned fusion approach a fusion feedback strategy will be investigated. The combination of information from different sensors on a high level of abstraction will be used to back-propagate the fusion-results to the single sensor specific algorithms. There, the information will be used to readjust and improve the sensor specific performance
Based on what described before, the general framework for DF is shown in the figure below:

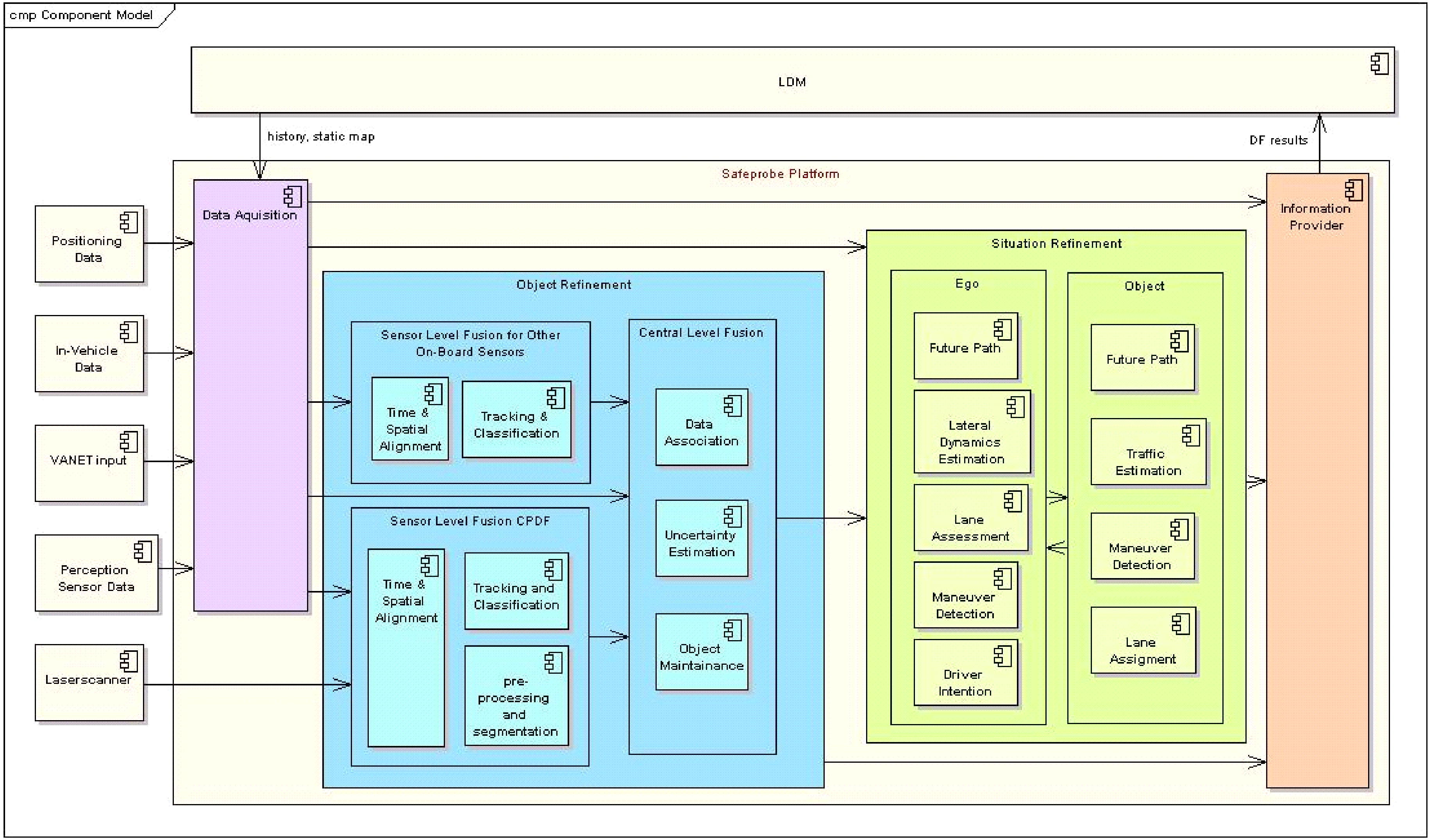


In SAFEPROBE project, we have developed an approach based on the use-cases and applicative scenarios identified in the early stage of the project, taking into account this general scheme identified by PROFUSION project.

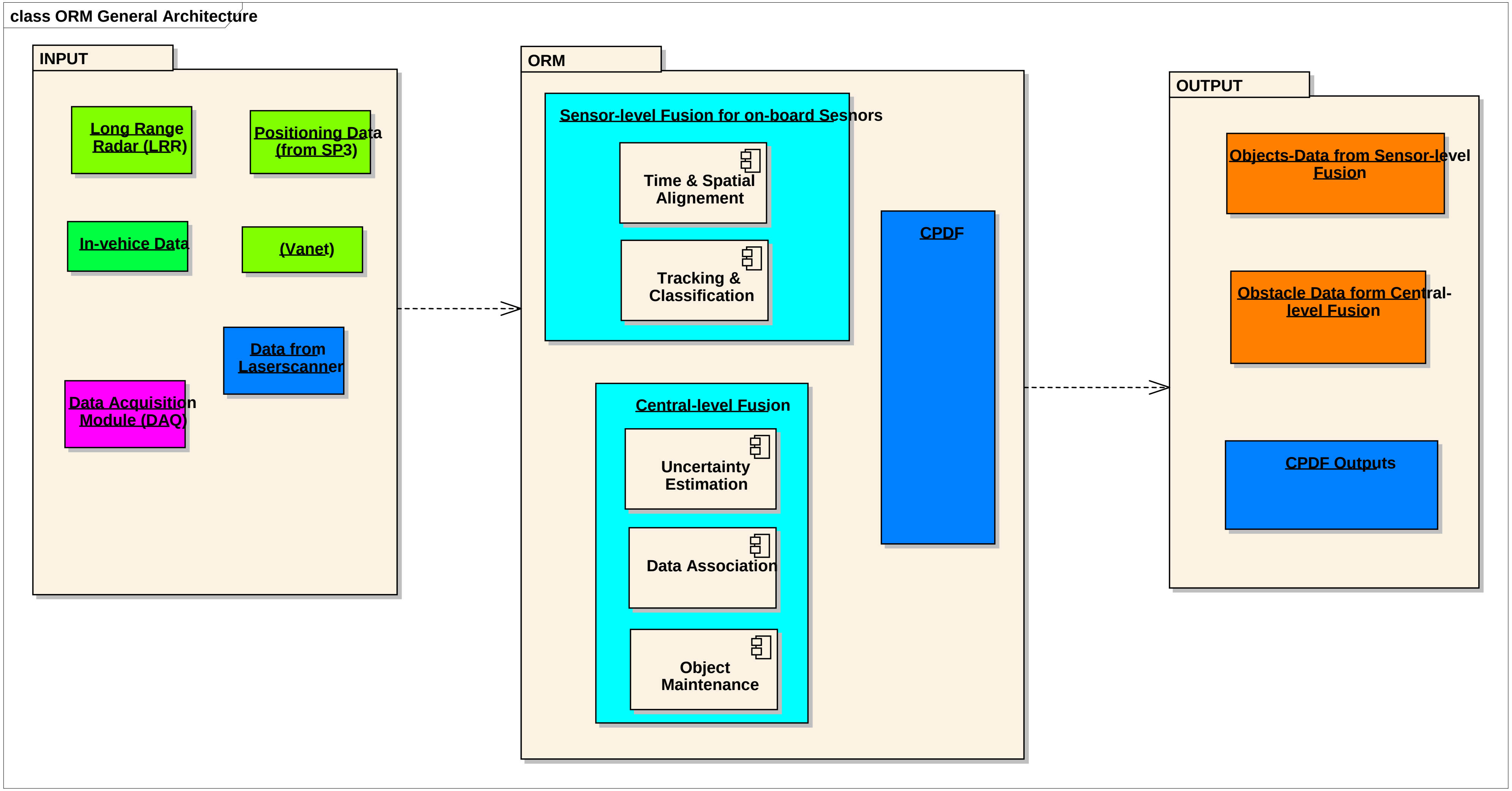
8. Appendix B – SF Node Functional Component Diagram (Guyancourt Diagram)



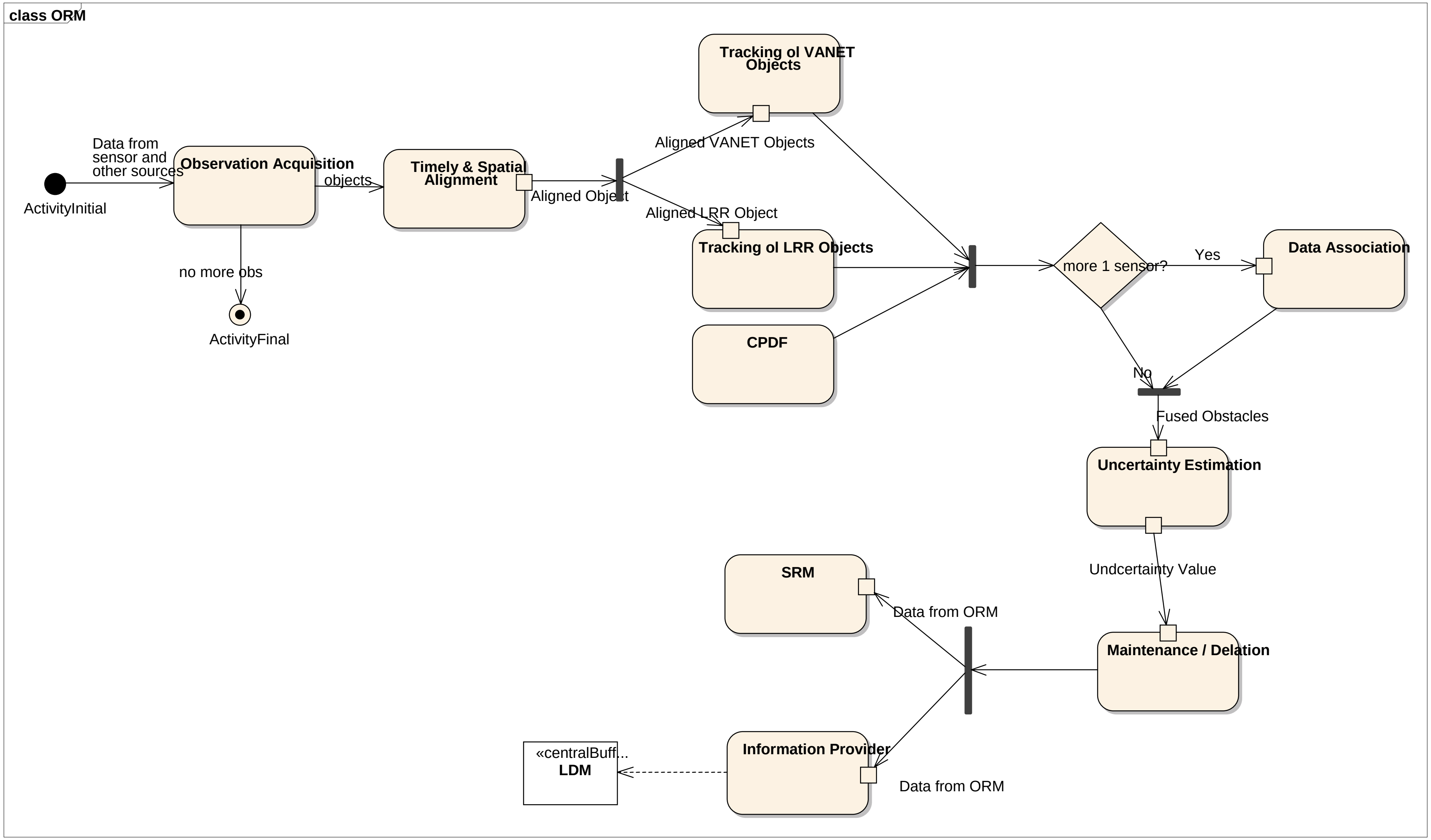
9. Appendix C – DF_functional component diagram



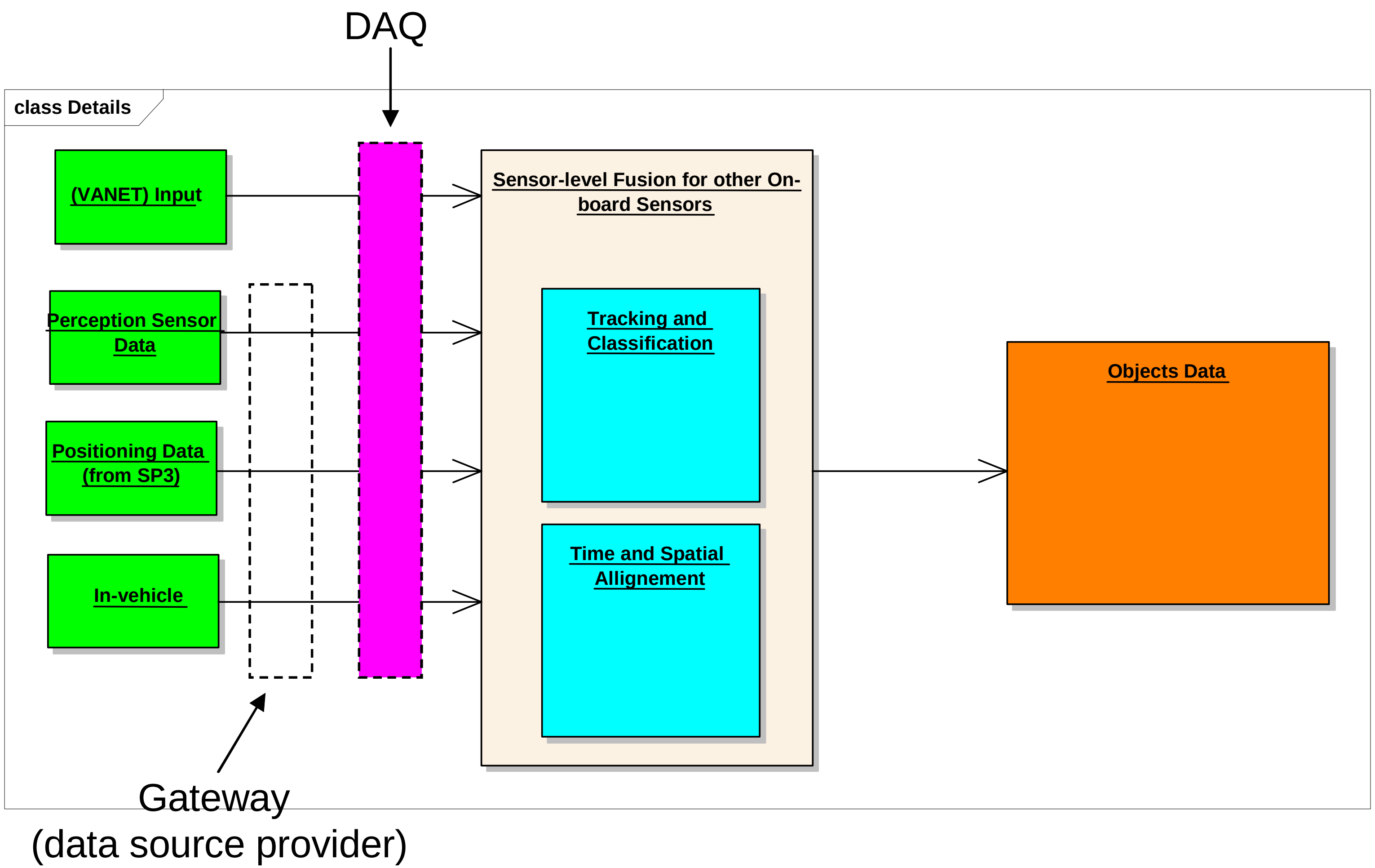
10. Appendix D – Main components in ORM architecture



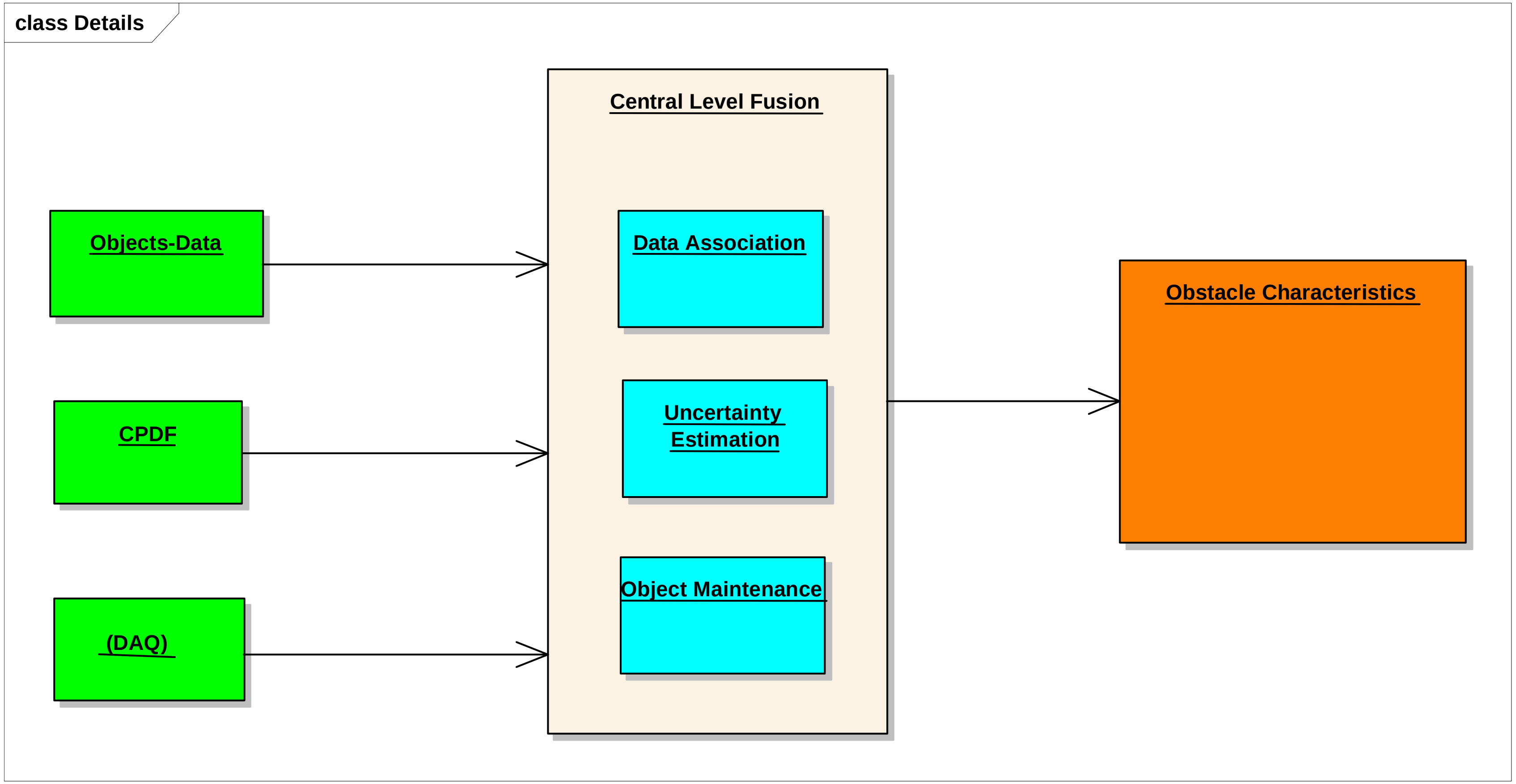
11. Appendix E – Activity Diagram for ORM



12. Appendix F – component diagram for SFOS



13. Appendix G – component diagram architecture for CL



14. Appendix H – Situation Refinement Module