ProFusion2 – Towards a modular, robust and reliable fusion architecture for automotive environment perception

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Abstract

This publication focuses on a modular architecture for sensor data fusion regarding to research work of common interest related to sensors and sensor data fusion. This architecture will be based on an extended environment model and representation, consisting of a set of common data structures for sensor, object and situation refinement data and algorithms as well as the corresponding models. The aim of such research is to contribute to a measurable enhancement of the output performance provided by multi-sensor systems in terms of actual availability, reliability, accuracy and precision of the perception results. In this connection, investigations towards fusion concepts and paradigms, such as 'redundant' and 'complementary', as well as 'early' and track-based sensor data fusion approaches, are conducted, in order to significantly enhance the overall performance of the perception system.

1 Introduction

In the European member states there are about 1.200.000 traffic accidents a year with over 40.000 fatalities. This fact points up the growing demand for automotive safety systems, which aim for a significant contribution to the overall road safety. For this reason a current technology field of the automotive industry focuses on the development of active safety applications and advanced driver assistant systems. These aspire a reduction or at least an alleviation of traffic accidents by means of collision mitigation procedures, lane departure warning, lateral control, safe speed and safe following measures.

The common nominator and key feature of all this novel safety systems is the accurate, robust and reliable perception of the vehicle's environment. However, current off-the-shelf single sensor approaches cannot always fulfil these challenging demands. Therefore most of these applications base on perception systems, which process the data from multi sensorial platforms via data fusion methods.

The Preventive and Active Safety Applications project (*PReVENT*), which is part of the Sixth Framework Programme, contributes to the safety goals of the *European Commission* (EC). *PReVENT* addresses the function fields of *Safe Speed and Safe Following*, *Lateral Support*, *Intersection Safety* and *Protection of Road Users and Collision Mitigation* in order to cover the field of active safety. The majority of these functions are characterized by using perception strategies based on multi-sensor platforms and multi-sensor data fusion.

Hence, the strategy of *PReVENT* was to initiate a cross-functional subproject called *ProFusion* in order to streamline and to develop the subject of multi-sensor data fusion in a greater degree of depth and in a more systematic approach as compared to the primarily function-driven subprojects. The role of *ProFusion*, inside *PReVENT*, is to streamline the sensor data fusion by, e.g. gathering requirements, defining certain standards and developing fusion algorithms.

In this context we propose a multi sensor fusion architecture, which facilitates the robust and reliable processing of multi sensor data by providing different data fusion approaches, a common data structure and a common modelling within one framework. Due to the special design of the framework and the underlying algorithms it is not limited to a single use-case but can serve as a modular platform for environment perception and thus build the basis for different kinds of safety applications.

An additional rationale is motivated by the observation, that a variety of national and international research projects are devoted to the development and improvement of active and preventive safety systems, and that all of them are affected by the limited performance and even by deficiencies of the currently available sensor platforms. As *PReVENT* is considered as the core of the *eSafety* research and development initiative, it has been obvious to embrace a cross-functional subproject that adopts a variety of challenges and open issues in the field of multi-sensor perception.

2 The Fusion Architecture

As already outlined in the introduction the perception of the vehicle’s environment is the crucial factor of a driver assistance and active safety system. Therefore the major objective of the conducted research is to push the sensor data fusion techniques used for automotive environment perception beyond the current state-of-the-art (cf. [6], [7]). This will be done by setting up a modular and interoperable fusion architecture for multi sensor systems, which integrates diverse approaches (e.g. low and high sensor data fusion, algorithms for situation refinement, etc.). In doing so the proposed framework is not limited to any special safety function but operational with all different kinds of applications like collision mitigation, lateral control, lane departure warning and others.

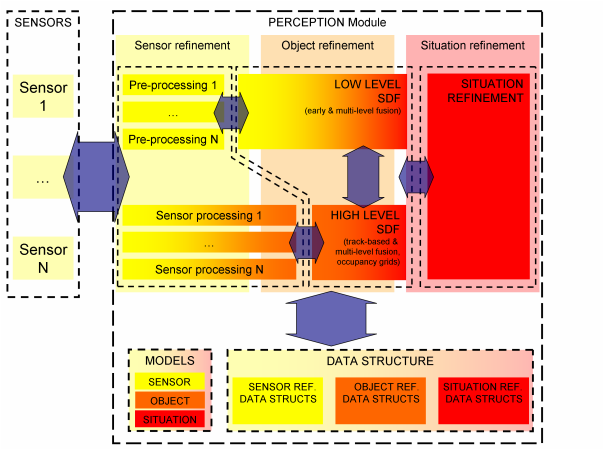

Figure 1: The sensor data fusion architecture

Figure 1 outlines roughly the concept and the components of the sensor data fusion framework:

The system will be based on an extended 4D scene / environment model (cf. [1]). Objectives are to deliver an extended view of the environment to applications (in terms of more detailed representations) and to define data structures for each processing step during the fusion process (e.g. for raw sensor data, signal features, objects detected in the environment).

For object refinement (cf. [2]), one will develop existing and new algorithms for filtering, data association and object classification. Especially, chances for deducing confidence information from complementary and redundant sensor data for each processing result will be analysed. Additionally, the research work will be focused on new motion models.

Research topics on situation refinement will include trajectory classification and prediction for objects on the road, trajectory estimation of the ego-vehicle based on multi source information (e.g. detected lanes, ego-vehicle dynamics and map data), as well as on generic decision components for the prediction of the driver’s intention.

The newly developed perception system (cf. [3], [4]), and especially the different fusion approaches, will be implemented, integrated and evaluated in open-loop real-time environments, and ultimately utilised in the closed-loop on-board systems of prototype vehicles (owned by BMW, CRF, DaimlerChrysler and Volvo Tec). These vehicles are equipped with distinct sensor platforms (including stereo vision cameras, FIR cameras, short and long range RADAR devices and LIDAR sensors) and serve diverse active safety application (see [5]).

The succeeding paragraphs describe the main components of the fusion framework, especially the different fusion approaches, in detail.

2.1 The Early Fusion Approach

The term "early fusion" is derived from a fusion concept, which is based on only slightly pre-processed data. They are processed together from an early stage of the processing chain. Such an approach permits the fusion module itself to process all data from the different sensors "as a whole". Taking use of the redundant sensor information and matching these data to one common and consistent scene model of the environment it should be feasible to slash inconsistencies and to increase the robustness and reliability of the processing results.

Thereby an early fusion system is working as follows: Several sensors deliver raw sensor data, for example echoes from RADAR devices, images from vision devices or FIR cameras, etc. to the sensor pre-processing unit. During sensor pre-processing specifics of sensor signals are extracted (peaks, plateaus, regions with same properties, etc.) and grouped. The resulting features can be provided in different abstraction levels. Based on these features objects are detected, classified and tracked over time in further processing steps.

All processing steps make, more or less, use of presumptions related to the vehicle environment. These presumptions, stored in models, should be consistent in the whole processing sequence. Thus beside the one common environment model of the early fusion module there should not be used any other model in other processing steps. Therefore the input data to early fusion are required to be based on the same models or, if not possible because pre-processing is contained and hidden in sensor components, to be based on minimal assumptions. As already indicated before, early fusion does not implicate to handle only some first processing steps, but takes data from early processing stages from all sensors, fuses and processes them together to one common result, the environment description of the vehicle.

Thereby the early fusion module is internally composed of several functional units, which are necessary to put the fusion process into practice. Figure 2 illustrates the different components of the fusion module and shows their interaction. It mainly shows the circle of processing steps that have to be executed:

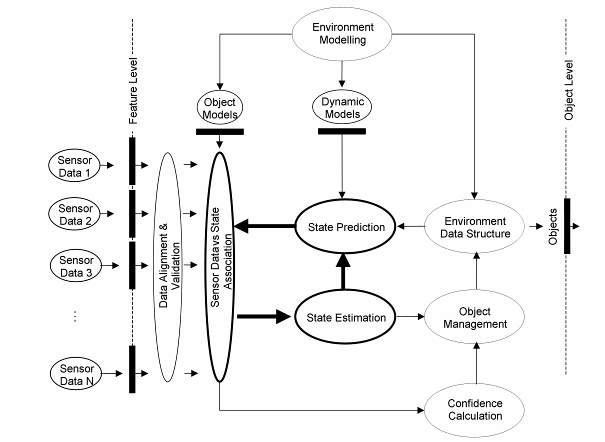

Figure 2: Early fusion functional architecture

The following paragraphs develop the functionality of the fusion module's components in more detail:

The process of sensor data association or matching is a key challenge of the early fusion architecture. Like in other fusion systems feature vectors are extracted from the sensor output data. In the matching step these feature vectors have to be assigned to the respective corresponding objects in the modelled track history causing the measurement data of the feature vectors. In track fusion systems the data association is done based on the pure object data from the sensor processing units and the object data from track history. In the early fusion module the data association poses the challenge, as this matching step has to be done for data on different level of abstraction, i.e. for edge to edge association up to edge to object / track assignment. Similarity measures are used to find the most probable and reasonable assignment of the acquired sensor data to the data of the object's history. Therefore they assess the association of the features based not only on their (Euclidian) distance, but in consideration of their covariance information and the origin of the sensor data.

As the early fusion approach is model driven, a further task of the matching module is the attribution and classification, respectively, of sensor data or features to different object models, which provide the basis for the characterisation of the environment. In the initialisation phase the matching module generates object assumptions for new features based on a set of given (shape and measurement) models (e.g. for the road, other cars and trucks, pedestrians, etc.) and allots the sensor data to the respective model that proves to be the most probable relative to the other ones. With the help of additional sensor data the respective object assumptions are either confirmed or discarded and newly reassigned over time. Whenever new features from the perception devices are available, the system checks if they can be associated to already existing objects in the environment description or if they are enough significant to create a new object assumption.

The handling and management of features, objects and tracks takes place in the environmental data structure. In this structure all information on the own car, the multi sensor system and the surrounding environment is stored just like the relations between these objects. Main task of the object management module is the addition, updating, fusing, splitting and deletion of features, objects and tracks to/from the environment data structure on the basis of new measurement data, data association operations and object hypotheses.

For the step of state estimation and prediction a realisation of the Extended Kalman filter is to be intended due to his simplicity, optimality and tractability in tracking and estimation of (non-linear) systems

The goal of the fusion module is to provide an as detailed as possible description of the own vehicle's periphery. This description, which contains all detected objects / tracks together with their attributes as well as their spatial interrelation in the surrounding area of the vehicle, can be easily generated at any time from the environment data structure. The format of the fusion module's output is generic and can be adapted to fit the respective application.

2.2 The Multi Level Fusion Approach

The holistic representation of the environment on the basis of the extended 4D environment model and the common data structures allows sensor data processing with the help of a multi-level fusion algorithm. Multi-level fusion means that not only one level of fusion exists but data components belonging to one physical object are scattered over different levels and evidently fused on several different levels too e.g. signal level, feature level and track level.

In general the chosen level of fusion is object and model dependent. Therefore for every object a certain hierarchical fusion strategy can be defined. This way the object tracking has inputs from tracked features, untracked features as well as from signal level.

A typical property of multi-level fusion is the use of back loops between the levels. Therefore feature models are used to describe which data from which level should be used to maintain an object track. This is organized by the multi-level fusion management. A special case of multi-level fusion is a processing on adaptive chosen levels. This allows the fusion strategy and selection of a certain fusion level to be dependent on the actual sensor data and the observation situation of an object. That's why a better processing strategy can be achieved in most cases.

The multi-level fusion approach means that several levels of fusion exist. Information and data which are generated by a specific object in the real world scene are fused on several different levels of abstraction. There are data components on the signal level, the feature level and the track level. At signal level all raw or pre-processed data coming from single sensors can be found. The data produced by different sensors are forwarded to the processing chain where they are processed and fused with data from the same, higher or lower level (see Figure 3: Multi-level fusion functional architecture).

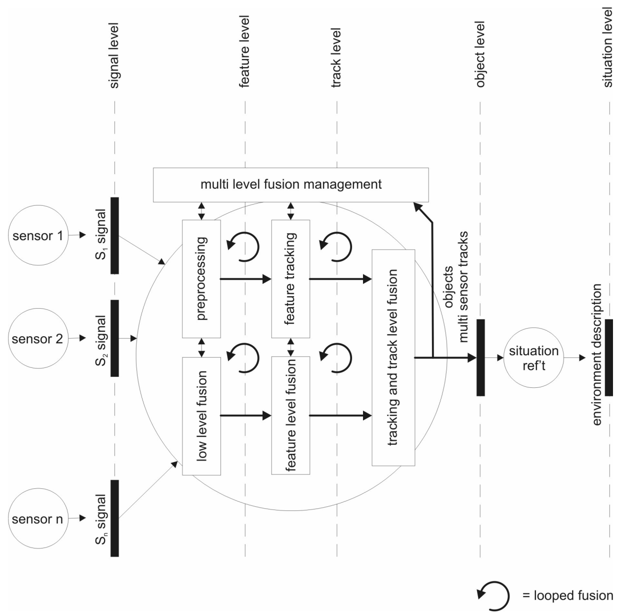

Figure 3: Multi-level fusion functional architecture

Multi-level fusion can be performed in two oppositional ways – a bottom-up or a top-down strategy. Both strategies can be used at the same time parallel and sequential in the processing chain. By performing the bottom-up strategy**,** specific model knowledge about a real world scene and its objects is used to fuse more or less primitive objects to primitive objects at the same or at a higher level.

In the case of a top-down strategy the model of an object contains all relevant information about its physical properties called features (e.g. its shape or its composition by components / structural information). Of particular interest is the information about which component can be detected by which sensor. Using this knowledge about a possible object the data of a lower level can be thoroughly analysed to increase or decrease the confidence in the assumption made before.

There are three options to design the general fusion structure. This is sequential fusion, parallel fusion and a looped fusion structure. These are three basic structural mechanisms that are in real systems combined with each other: In a sequential processing approach the chain of data processing can be followed bottom up level by level performing fusion operations between data elements that come from the same sensor. Due to this strategy the degree of fusion as well as the degree of confidence is increased continuously. The second option – parallel processing chains – occurs, if several sensors are available and if parallel alternative processing is performed for the same sensor. Then the degree of composition increases, because components delivered from different sensors are combined and the sensor specific confidences are accumulated. Looped fusion can be implemented if detected features are assigned to a feature model and a back loop according to the degree of composition is initiated. Doing that it should be possible to assign additional features defined by the feature model to the object hypotheses. The use of feature models and the mentioned methodology allows increasing certainty and confidence of object estimations by the perception process itself. If the quality of the interim results is not satisfactory the data can be passed through an adopted processing chain again to improve the results. The back loops are located between several levels. The repetition of certain processing steps can result in more accurate and stable results.

The state of the whole system represents a certain scenario in the real world how it is seen by multiple sensors. This overall information is the content of the environmental model. The environment description is a specific output of the environment model. This description can be used by an application to process certain information of the 4D environment model.

2.3 The Grid-based Fusion Approach

The main idea of grid-based fusion is to do sensor data fusion in an occupancy grid. This occupancy grid is a regular discretisation (sampling) of the environment in cells, where each cell contains the probability that the corresponding part of the environment is occupied. Sensor data fusion is done in a generic way in occupancy grid framework. This approach allows an important sensor flexibility and sensor independence. Sensor data fusion could be done at different levels: at a feature level, in this case, a precise model of each sensor is needed to build the grid, and at a track level, in this case, a geometric description of the processed data is needed.

The resulting occupancy grid is actually a snapshot of the current environment, i.e. an instantaneous view of the surrounding environment of the vehicle at a fixed frequency. In an occupancy grid, each cell contains the probability that there lies an obstacle. Advantages of the occupancy grid framework:

- the framework is sensor independent
- the framework could deal with raw data (low level fusion) and with pre-processed data (high level fusion)
- fusion of sensor data in each cell of the grid
- priors (i.e. the initial probability for each cell) according to the occupancy of the whole space could be integrated; For instance, if we are in a crowded environment, the prior of occupancy is very high and the rate of false alarm and missed detection is very high, and the fault tolerance of the system is increased

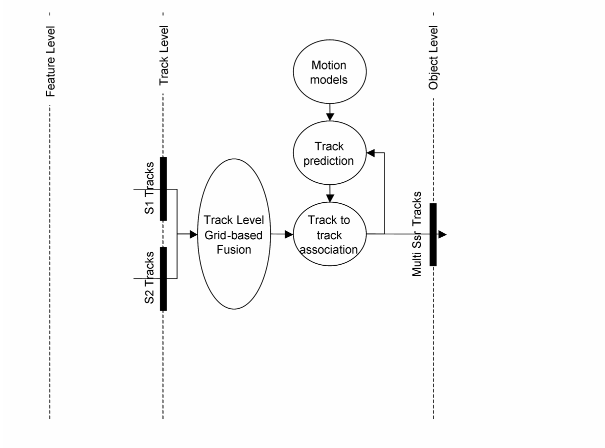

Figure 4: Detail of the grid-based fusion architecture on the track/high level

In the case of high level fusion, the sensors return for instance velocity, of which a map of velocities is built as in an optical flow framework according to the discretisation of the occupancy grid. Thus in each cell, a probability distribution over a set of possible discretised velocities is built. If the sensors can return a classification of the obstacles, a map of category (such as car, truck, bicycle, pedestrian, none) is established and in each cell a probability distribution over all the possible categories is set up.

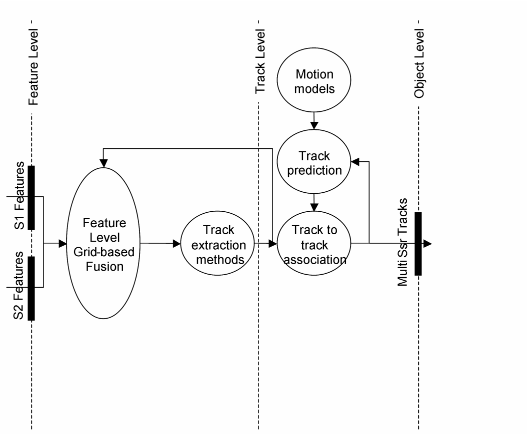

Figure 5: Detail of the grid-based fusion architecture on the feature level

Based on the occupancy grid, we extract the objects in the grid: Moving obstacles are extracted by first identifying the moving area. We proceed by differencing two consecutive occupancy grids in time. Then extraction of features such as surface and velocity could be performed to classify the type of obstacle. In case of the possibility of using velocity or a category map the previous process is fused with these two maps to obtain the gravity centre of each object and a probability distribution over its possible category.

Data association algorithms are used to update the different tracks with extracted tracks. To deal with unobservable tracks, we use a particular process for handling occlusions. To deal with the particular topology of the environment: entry and exit areas, we use a particular process based upon the roadmap.

Thanks to the occupancy grid, we extract unobservable areas due to occlusions (Occlusion management). For each object, three cases arise:

- The object is seen by the sensors and then is associated with sensor measurement.
- The object is not seen due to occlusion, the sensors measurements define occluded areas and in each occluded area there is a uniform probability that the object lies.
- The object is not seen due to miss detection. When association is made, a probability over the velocity and the category is updated thanks to prediction models for each category of road users.

Thanks to the interpretation of the map, we are able to know areas where the objects could appear or disappear (entry and exit areas). This helps the robustness relative to false alarm and missed detection.

Object list are managed as a list of tracks. Each track is tagged with a specific ID and a set of characteristics. A track is created when consistent sensor information makes the existence of an object certain. One deletes a track only if this track disappears of the sensor view in a disappearance area. We also manage merge and split of objects and all other relevant problems that might appear. To perform the tracks update, tracking methods are used and a set of hypotheses of predicted position, velocity and category for each object is obtained.

In the situation refinement, we propose to perform trajectory prediction for the objects present in the environment. This trajectory prediction is performed using the classical “learn & predict” paradigm. In a first step, the past trajectories of the objects are collected and are clustered to define some classes of typical trajectories. In a second step, these classes are used to predict the future trajectory of an object present in the environment.

2.4 The Track-Level Fusion Approach

The track-based fusion within the object refinement layer is a distributed approach. It assumes that tracking is carried out inside each individual sensor or system, and the tracks feed the track level fusion algorithms. It can be applied to automotive sensor networks with complementary or/and redundant field of view. The advantage of the approach is that it ensures system modularity and allows benchmarking, as it does not allow feedbacks and loops inside the processing.

Research and development for track level fusion is focused on developing innovative algorithms in the area of multidimensional (N-D) track-to-track association, track management and track fusion. Expected results from these efforts are more consistency and the avoidance of spurious or invalid perception information. The output of the track level fusion is aggregated tracks in the union of the sensor field of views.

The research and development process for situation analysis consists of two main components: The first step is to develop the appropriate level of domain specific knowledge for the road elements (e.g. road borders, lanes, obstacles) and the second to develop a decision making process that is able to codify and manipulate the knowledge mentioned above. In situation refinement the system is aware not only of the states of the road elements but has also knowledge of their relationships. The outcome of situation refinement enriches the environment model including additional attributes of the ego-vehicle and the obstacles (predicted paths, object to lane assignment, evidence for vehicle manoeuvres, etc.)

The track level fusion architectural modules are depicted in the figure 6. It is implied that a set of track arrays are entering the fusion system while the output of object refinement process is consisted of the fusion object list. The internal functionalities in this architecture are the association (spatial track assignment and 2-D and N-D association), the track to track update (fusion) and the fused object management. All these sub-modules are described in detail in this section.

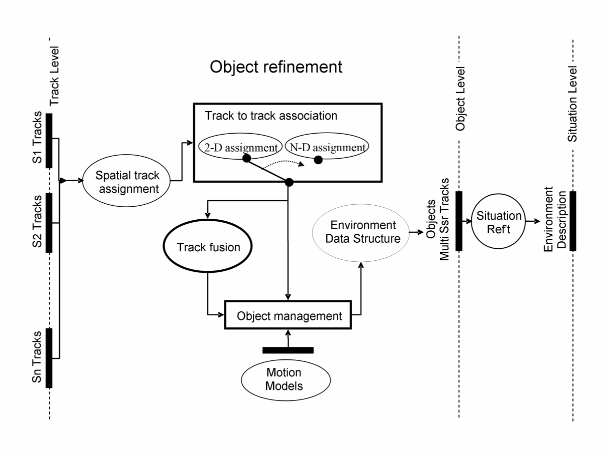

Figure 6: Track-based fusion functional architecture

The Fusion Area Track Assignment is the first function that is imposed to the tracks when they are entering the fusion system. The main objective of this is to decrease the computational load of the overall procedure and also to ensure the configurability and the interoperability of the procedure. A set of sensor configuration parameters are necessary for this module to work properly. At least it is required to have the sensors' maximum range, Field Of View (FOV), direction, location, accuracy resolution and a performance index - estimation error covariance matrix or overall confidence level. The main process of this module is to separate the sensor coverage area around ego vehicle and consequently to separate the available tracks. These areas could be blind areas not observed by any sensors, areas with one sensor and areas observed by two or more sensors. The main result of this process is to divide the fusion problem to a number of smaller fusion sub-problems.

The tracks that belong to areas without or single sensor surveillance are passing to the output without any additional processing. On the other hand, the tracks that are within the common sensors areas (2 sensors or more) an association measure will be defined. This metric is for generating the hypotheses for association between tracks, and then the relative association matrix or other metric passes to the next level where the track to track assignment takes place (Track to Track Association). In the case of 2 sensors tracks the 2-D association problem is solved. The input to this module is the output of track to track association and its output is the pairs of tracks that are suitable for fusion and the not assigned tracks that simply pass to the next module. In the case of tracks coming from more than 2 sensors then the solution to this problem the N-D with N to be 3 more takes place in this module. Usually this problem concerns the sequential generation of a 2-D problem out of the N-D and after that the solution is similar to this acquired in 2-D assignment.

The assignment tracks (2 or more) that come from the output of the assignment modules are fused by the track fusion module. They are updated and generate a fused object state and covariance that replaces the existing sensor level tracks.

Within the object management module the fused and the non-fused tracked objects are formatting the final object list output for the object refinement process. All the objects have an ID and in this module the initialisation, updates, deletion of objects based on ID information take place. Moreover, this module will handle, in a final step, object management issues such as duplications of objects, blind areas objects, transition of objects between different areas and all other relevant problems that might appear.

The model collection, containing also motion models, is a horizontal activity and not only internal in object refinement. It is a function that generates and uses the available dynamics models, static models, sensor models and the relative to the environment description models. This module is also necessary to the situation refinement process.

The internal situation refinement modules are depicted in the figure 7. The output of the object refinement process is the main input in this module. The internal functionalities that take place in this architecture are the assignment to objects in a specific lane and the prediction of the path of the ego and the other vehicles (moving objects). The final output is the ego-vehicle and moving objects manoeuvre classification together with a confidence index. The output of this module passes to the application.

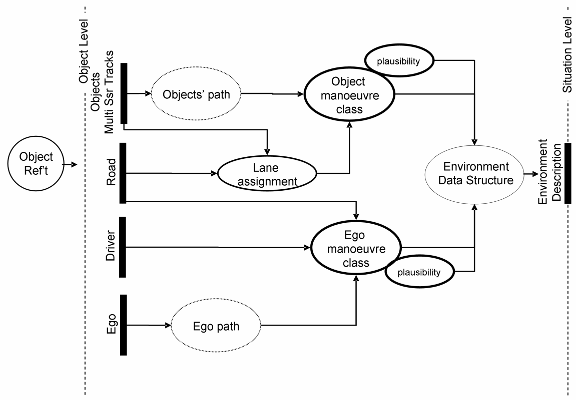

Figure 7: The situation refinement internal functional module architecture

The object path module and the ego path module concern the prediction of the expected future path of moving vehicles and the own car respectively for a short period of time (e.g. 4s).

The lane assignment module uses object position information and the available lane geometry and assigns a lane index to each of the vehicles accompanied with a confidence index. This information is very useful for the manoeuvre classification modules.

The objects and ego manoeuvre classification modules analyse the behaviour of objects and the ego vehicle and classifies them according to a predefined discrete set of classes (e.g. overtaking, exceeding speed, parallel to the lane, lane change, etc.). These modules assume the existence of an environment model – i.e. descriptions of the road attributes and the lane properties and the output of the objects' path and the lane assignment; they analyze relationships between "objects" and produce a new structure. Their output will be part of the environment model and will be defined in the relevant tasks. The decision is accompanied with a level of confidence.

2.5 The Fusion Feedback Approach

To overcome a limitation of track-based fusion, some approaches insist on injecting information coming from other sensors at an early stage of processing by a given sensor. This can be achieved by feeding unprocessed – or slightly processed data – from different sensors into a single module in charge of all processing across different sensors.

An original alternative way put forward here relies on fusion feedback. In track-based fusion architectures, taken as reference architectures, the output of fusion reflects information coming from different sensors. By feeding this processed multi-sensorial information into early processing of a given sensor (here sensor 1), we make it possible to sensor 1 processing to confirm some detection formerly only suspected by sensor 2.

As an example, a RADAR device and a FIR camera originally produce tracks. Track-based fusion will merge some of them, and logically leave some RADAR and FIR tracks unmatched, because of possible complex and/or misleading environment. With Fusion Feedback, the RADAR information available on output from Track-Level Fusion will allow FIR processing to further rescan the area corresponding to the RADAR-only tracks.

Fusion Feedback builds upon a track-based fusion architecture, providing a solution to overcome its limitations through little structural changes. To do so, we want the processing of some given sensor – sensor 1 – to be able to use some additional information including data from sensor 2. The output is an excellent candidate, as it already exists in a traditional track-based fusion architecture. It contains information provided by both sensors.

Therefore, we feed the output of track-based fusion into sensor 1 processing, as illustrated by the figure 8. Here, information coming from sensor 2 goes to track-based fusion, where some sensor 2 tracks might be left unmatched for various reasons. However, sensor 1 processing will use this information to better focus its search. This concept provides improved performance, without major reshuffling of the track-based fusion architecture, as it merely requires one additional link from fusion to the sensor processing, and customisation of the sensor processing.

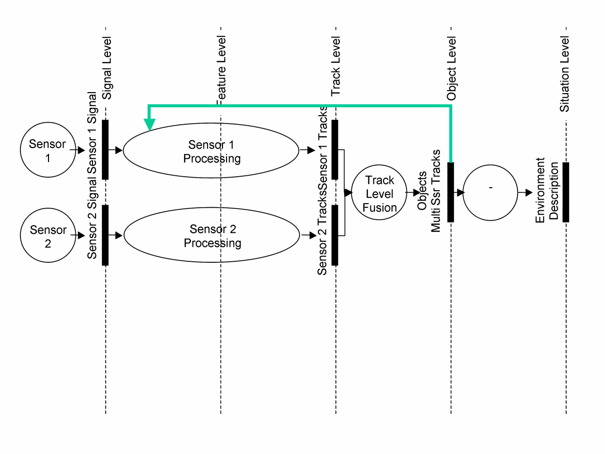

Figure 8: Global Fusion Feedback architecture

According to the addition of the link illustrated in the Figure 8, the sensor 1 processing must be able to take advantage of information coming from track-based fusion. Considering a FIR camera as sensor 1 the original sensor 1 processing can be described as acquisition, pre-processing, detection, tracking and output formatting. Now, to accommodate the use of extraneous information, we have to enhance this architecture with additional sub-modules, and some enhanced existing sub-modules (cf. figure 9).

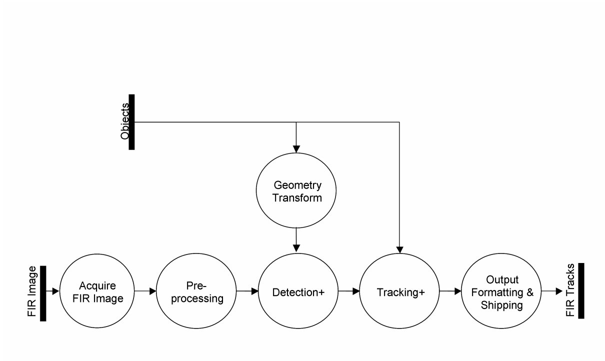

Figure 9: Modified detection scheme

The information coming from the fusion module has to be converted into the natural representation for the sensor, here the FIR camera. Then detection must take into account the hint provided, possibly by releasing detection thresholds around given areas. Beside its usual functionality, tracking will now additionally have to check the compatibility between external track continuity and possible new FIR tracks detected using this hint.

3 Conclusion

In this paper we presented a modular framework for multi sensor data fusion, which addresses the crucial task of automotive environment perception. Thereby this interoperable architecture is not dependant on a special safety application but is designed on top of a multi sensor platform to serve diverse safety functions at once. Furthermore it will offer a robust and reliable perception performance due to the integration of diverse fusion approaches and algorithms for situation refinement beyond current state-of-the-art. Additionally this architecture with its extended environmental modelling provides an excellent basis for further enhancement in the field of automotive environment perception and thus contributes to the design and development of road safety systems.

Acknowledgement

The work described within this paper is part of the results obtained in the *ProFusion2* project, which is a subproject of the *PReVENT* Integrated Project, an automotive initiative co-funded by the European Commission under the 6th Framework Program. The long term goal of the subproject *ProFusion2* is to streamline the sensor data fusion inside *PReVENT* by, e.g. gathering requirements, defining certain standards and developing fusion algorithms, which should be used by the application-oriented subprojects within *PReVENT*. Hence *ProFusion2*, whose consortium consists of CRF, DaimlerChrysler, Delphi, FORWISS, IBEO, ICCS, INRIA, SAGEM, the University of Chemnitz and Volvo Tec, addresses research work of common interest related to sensors and sensor data fusion including a modular architecture for sensor data fusion. This architecture will be based on an extended environment model and representation, consisting of a set of common data structures for sensor, object and situation refinement data and algorithms as well as the corresponding models.

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