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High Level Sensor Data Fusion Approaches For Object Recognition In Road Environment

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Abstract—**Application of high level fusion approaches demonstrate a sequence of significant advantages in multi sensor data fusion and automotive safety fusion systems are no exception to this. High level fusion can be applied to automotive sensor networks with complementary or/and redundant field of views. The advantage of this approach is that it ensures system modularity and allows benchmarking, as it does not permit feedbacks and loops inside the processing. In this paper two specific high level data fusion approaches are described including a brief architectural and algorithmic presentation. These approaches differ mainly in their data association part: (a) track level fusion approach solves it with the point to point association with emphasis on object continuity and multidimensional assignment, and (b) grid based fusion approach that proposes a generic way to model the environment and to perform sensor data fusion. The test case for these approaches is a multi sensor equipped PReVENT/ProFusion2 truck demonstrator vehicle**.

I. Introduction

THIS paper presents part of the work taking place in the IP PReVENT ProFusion2 subproject concerning the development of data fusion algorithms for object refinement. This includes the issue of managing information, from multiple sensors, in a common platform for advanced vehicle applications extracting high level information for typical objects of road environments.

Even though there is a dispute whether solely vision sensors are adequate to support the automotive safety applications [1], there seems to be a wide recognition that both range sensors like radars and lasers are absolutely necessary. The only obvious solution towards simultaneously exploiting this multisource and heterogeneous amount of information is data fusion. First ADAS applications were operating with a single sensor in a specific topology, but as more applications are integrated in the vehicles more sensors are deployed as well. Thus, data fusion has to be applied; in order to handle this redundant and complementary information ensuring the extension of single sensor efficiency and making system design economic as a set of applications would share the same sensors [2].

However, the unanimous acceptance of sensor data fusion (SDF) has generated in turn a series of new arguments for which SDF architecture is the most appropriate. The main architectures are the High Level Fusion (HLF) approach where an amount of processing (tracking) takes place in sensor level, and the Low Level Fusion (LLF) approach with the main processing of raw sensor data to take place in a central level. Both approaches demonstrate a set of known well advantages and disadvantage (e.g. [3]), but the heterogeneous information of automotive systems changes significantly the situation. Supporters of LLF claim that the main shortcoming of HLF is that the performance of target's class identification is deteriorating after the processing of single sensor data, and that the great amount of computational load is paid off with the better results in object detection and classification using all the available information [4]. On the other hand, researchers in favour of HLF argue that this approach offers modularity and allows benchmarking and substitution of sensorial systems as it does not allow feedbacks and loops inside the processing. Consequently, HLF requires less computational load and communication resources. Yet, in HLF arises the issue that some times the implied modeling of sensor level information is vague and even contradictory with the assumptions in the fusion processor [5], and certainly that the sensor level errors are depended with each other and should be taken into consideration.

Authors, who are supporters of HLF approaches, aim at overcoming the limitations referred above taking advantage at the same time of the many benefits of these schemes and at introducing generic solutions for SDF in the automotive area. In this paper two specific approaches of HLF architectures are proposed for the vehicle environment recognition. Track Level Fusion (TLF) by ICCS that follows the classical data association (DA) methods and Grid Based Fusion (GBF) by INRIA that proposes a generic way to model the environment and to perform sensor data fusion.

Related work on multi sensor data fusion for preventive safety has been carried out in a chain of research activities

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such as the ARCOS project [6] with a forward collision mitigation combining stereo vision and laser scanner, the EUCLIDE research project [7] which is a forward collision warning and vision enhancement application using far infrared and mmw radar sensor. The same sensor combination was used in the PAROTO project [8], while in the CARSENSE [9] project information from a radar, video sensors and a laser was fused. These first fusion systems in automotive safety where using a limited number of sensors and were focused in one particular application (e.g. forward collision warning). However, in IP PReVENT more sophisticated fusion systems are being tested with a group of integrated applications, characteristic example is the LATERAL SAFE subproject with eleven sensors observing holistically the rear and side areas of the vehicle [10]. In ProFusion2 innovative research on SDF takes place and prominent vehicle manufacturers offer useful test cases where several independent sets of sensorial systems are used. In this work the test demonstrator vehicle is a Volvo Technology Corporation sensor equipped truck. For the ProFusion2 application case, this vehicle comprises sensors with redundant field of view looking forward: long-range radar (LRR), a laser scanner, two short-range radar sensors, and a lane camera system.

II. Test Vehicle Application And Object Refinement Requirements

Within the ProFusion2 research initiative, high-level data fusion is investigated for the sensor set of the Volvo Technology demonstrator truck. Objective of the sensor signal processing is to provide a perception of the vehicle's environment to support the functionality of the PReVENT sub-project COMPOSE of collision mitigation by braking (CMbB).

Collision mitigation deals with the situation in the last second before a collision. If a collision has been detected to be unavoidable by laws of physics, it is crucial – particularly for a truck – to minimize velocity and thus crash energy before the impact. Therefore, the COMPOSE project aims at applying full brakes once a collision has been detected to be imminent. Additionally, the driver shall be warned before a collision to allow him to react, e.g. with a steering manoeuvre.

To apply fully automated braking to a truck in traffic scenarios, a substantial amount of reliability has to be provided by the environment perception to allow a safe decision. For this reason, a set of complementary sensors is investigated consisting of: a laser scanner, a long-range radar, two short-range radar sensors and a lane tracker camera system. All of the sensors observe the area in front of the truck; an overview is shown in Figure 1. The lane tracker system is intended to provide additional information about the ahead road curvature.

With respect to the collision mitigation application, the object refinement requirements are to provide an environment perception that is sufficiently reliable for this challenging application. A particular concern is given to reliability of object detection and a low false alarm rate of fused sensor data.

Fig. 1: Volvo FH12 demonstrator truck

It also is of interest to combine the information from different sources about the same object to better derive its properties and object classification. It is a further challenge to provide a generally better perception of the environment. Therefore, the track level fusion approach does not only comprise fused information about surrounding objects, but also takes lane tracker information into account to investigate the objects' position with respect to the own lane, allowing better warning strategies.

III. High Level Data Fusion Architectures

As already mentioned authors support the HLF approaches for managing the multisource and significantly heterogeneous information of multisensor equipped vehicles. Apart from the known issues HLF concerns also the topics of filtering and state estimation, having to deal with the complicated issues of data association that arise in such systems. These issues are discussed in sections IV and V in more detail, with a brief overview of their architectures to be given in this section.

A. *Track Level Fusion Architecture*

The main parts of the TLF algorithm as illustrated in Fig. 2 are: the time and space alignment of track arrays, the division of fusion sub problems according to the area covered by each sensor or sensor system, the track to track association procedure that is solved with 2D and S-D (if $S \geq 3$) assignment, the fusion object update from the pairs or S-ples of tracks and the object management that is the final step before the objects pass to the output.

The core of Track Level Fusion (TLF) is the track to track association algorithm. This plays a key role to the performance of TLF ensuring the continuity and maintenance of objects all around sensor covered area and the solution of multi-source objects assignment. Important part of TLF approach is the Sensor Tracking (ST) of single sensor measurements. The output of this procedure is the high level track information input to the TLF system illustrated in Fig. 2. The main characteristic of the ST algorithm that is developed is the capability with simple functionalities to deal with different sensors input (type, measurement, orientation) providing the best possible solution.

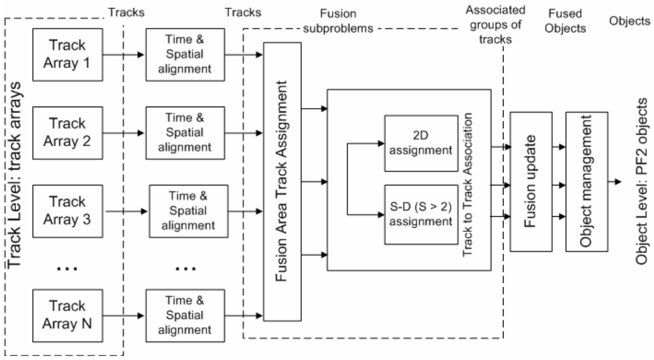

Fig. 2: Track-Level Fusion architecture

B. Grid Based Fusion Architecture

The idea of the approach called *grid based fusion* is to develop a new framework to multi-sensor fusion called occupancy grids (OGs) [12]. An OG is a stochastic tessellated representation of spatial information that maintains probabilistic estimates of the occupancy state of each cell in a lattice.

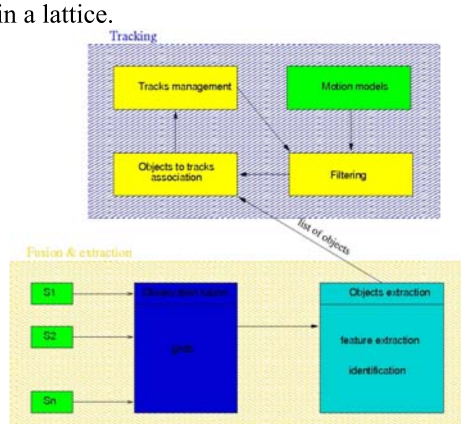

Fig. 3: The Grid Based Fusion architecture

In this framework, each cell is considered separately for each sensor measurement, and the only difference between cells is the position in the grid. The main advantage of this approach is the ability to integrate several sensors in the same framework, taking the inherent uncertainty of each sensor reading into account, contrary to the geometric paradigm. The major drawback of the geometric approach is the number of different data structures for each geometric primitive that the mapping system must handle: segments, polygons, ellipses, etc.

Taking into account the uncertainty of the sensor measurements for each sequence of different primitives is very complex, whereas the cell-based framework is generic and therefore can fit every kind of shape and be used to interpret any kind and any number of sensors. For sensor data integration, OGs only require a sensor model which is the description of the probabilistic relation that links a sensor measurement to a cell state, occupied (occ) or empty (emp).

As our objective is to have a robust perception using multi-sensor approaches to track the different objects surrounding a car, the grid based fusion approach is combined with multi-objects tracking techniques. The whole architecture is depicted in Fig. 3. This architecture is composed of two distinctive parts: a Grid based fusion and Extraction level and a Tracking level. In the first level, we perform mapping of the environment and fusion of data given by different sensors to build a map of the current environment .i.e. a snapshot of the current environment. In a second step, using this map, we search the objects currently present in the environment. Finally, in the tracking level, we associate this list of objects with the list of objects previously present in the environment. An implementation of the complete architecture could be found in [13].

IV. Track Level Fusion Approach

As written in Section III the key components of the TLF approach are the ST algorithm for the set of the available sensorial systems and data association module that should deal with all around object maintenance and multidimensional assignment.

A. Mathematic formulation

Skipping the well known equations of state estimation, we present here the formulations of the **multidimensional data association problem** [16]. Let regard that we have N data sources applicable for association with M_p observed values from each source p with p=1,2,...,N. Next the following quantity is defined $z_{i_1 i_2 \dots i_N}$, which corresponds to the hypotheses of association formulations, where observations $i_1, i_2, \dots, i_N$ come from the same target-source. For instance z_{322} refers to the fact that observation 3 of source 1, observation 2 of source 2 and observation 2 of source 3 come from the same target. If any index is equal to zero means that this source gives no detection. Thus the dual variable $z_{i_1 i_2 \dots i_N}$ for the association of an hypothesis is defined as:

$z_{i_1 i_2 \dots i_N} = 1$, track hypothesis is correct

$z_{i_1 i_2 \dots i_N} = 0$, track hypothesis is false

In a similar manner the cost of formation of associations $c_{i_1 i_2 \dots i_N}$ is defined. The prediction that the observation of source p is a false alarm has the following cost $c_{0 \dots i_k 0 \dots 0} = 0$. Taking all these definitions into consideration the problem of generation of associations using data from N sources is transformed into the subsequent optimization problem:

$$\max \sum_{i_1=0}^{M_1} \dots \sum_{i_N=0}^{M_N} c_{i_1 \dots i_N} z_{i_1 \dots i_N} \quad (1)$$

given that: $\sum_{i_1=0}^{M_1}\cdots\sum_{i_{k-1}=0}^{M_{k-1}}\sum_{i_{k+1}=0}^{M_{k+1}}\cdots\sum_{i_{N-1}=0}^{M_{N-1}} z_{i_1 \ldots i_k \ldots i_N} = 1,$
$\forall i_p = 1,2,\ldots,M_p, \quad \forall p = 1,2,\ldots N$

(2)

Equation (2) shows that all observations of source p should be taken into account only once in order to produce all possible combinations of the rest of the sources. The case that the associated sources are two is solved by known constrained optimization problems solution algorithms (e.g. auction algorithm [11]) for 1-to-1 assignment, and with possible the extension to probabilistic solutions. The not optimum but efficient solution to the multidimensional assignment problem is feasible with the method of Lagrange multipliers relaxation (e.g. [16]). This kind of solutions for our multidimensional DA problem (see Section II) is searched in the TLF research approach we investigate.

Track Fusion of distributed sensors data in HLF architectures is the next step in TLF approach. In TLF a set of N different sensors with M_N tracks from each one, after the generation of the associated groupings, let them be G of M_G tracks each, finally it gives the G ultimate fused objects together with the objects observed by solely one sensor. A track is consisted apart from the estimated state vector also from a quality measure, which usually is the covariance matrix of the estimation error. The track array coming from sensor n (n from 1 to N) is: $\{\mathbf{x}_1, \mathbf{P}_1\}, \{\mathbf{x}_2, \mathbf{P}_2\}, \ldots, \{\mathbf{x}_{Mn}, \mathbf{P}_{Mn}\}$

What is requested for each group of associated sensor level tracks is a fused track (object) that is a best estimation compared to each of the single sensors outputs individually. The estimation of the state and covariance of the fused object i (with i between 1 and G) that arrives from estimations of M_G sensors, let specify them as $\lambda_1, \lambda_2, \ldots, \lambda_{MG}$ (M_G from 1 to N) are functions of these parameters:

$$\mathbf{x}_{fused} = f_1\left(\mathbf{x}_{\lambda 1}, \mathbf{P}_{\lambda 1}, \mathbf{x}_{\lambda 2}, \mathbf{P}_{\lambda 2}, \ldots, \mathbf{x}_{\lambda MG}, \mathbf{P}_{\lambda MG}\right) \quad (3)$$

$$\mathbf{P}_{fused} = f_2\left(\mathbf{P}_{\lambda 1}, \mathbf{P}_{\lambda 2}, \ldots, \mathbf{P}_{\lambda MG}\right) \quad (4)$$

There are several approaches to find the most appropriate method to identify the best functions f_1 and f_2 in order the fusion requirements to be met [23][24][25].

B. System design

The several steps of design process of the TLF approach require firstly a robust ST algorithm for the single sensor data. Then the main fusion algorithm comes which is heavily based in the DA performance.

Therefore, ST for the different available sensors long range radar and short range radars, laser scanner and vision systems is developed. Moreover different topologies for each of them are applied. Processing of vision systems (e.g. image processing) does not takes place and data are taken from built-in systems. The same would be probably followed also for laser scanner, but testing is in progress. Sensor specific ST algorithms that take account for different object measurements, measurement models, object occlusions with small modifications are under development.

DA research work in TLF concerns techniques to handle various sources of object information from the available sources (e.g. multipoint objects, different quality). These include initialization of objects, generation of association metrics, two dimensional and multidimensional constrained optimization solution algorithms to solve the track to track assignment issue and object management approaches.

Two general categories of assignment problems are identified: the classical 2D assignment problem and the S-D (with S ≥ 3) [16]. The first is most common in the problems in the typical sensor topologies in automotive area but the second can be also observed in the cases of more than two sensors observe a common area, as happens in the Volvo test vehicle in ProFusion2.

These two algorithms and their switching selection are adequate to solve the 1 to 1 assignment problem in 2D data association. 2D data association is completed with the integration to the overall algorithm for the case 1 to N assignment. The case of 3 or more sensors observing a common area was also investigated. The typical Lagrangian relaxation (e.g. [16]) method is used to solve this multidimensional data association case. The process of sequential relaxation of constraints and reduction in subproblems of lower dimension and then the Lagrangian multipliers update phase until an assignment solution will be found, is illustrated in Fig. 5.

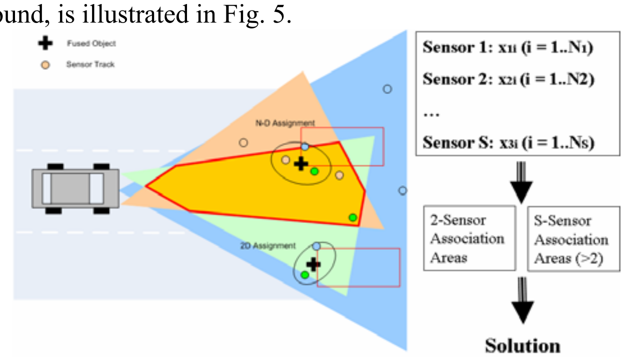

Fig. 4: Data association cases in automotive area

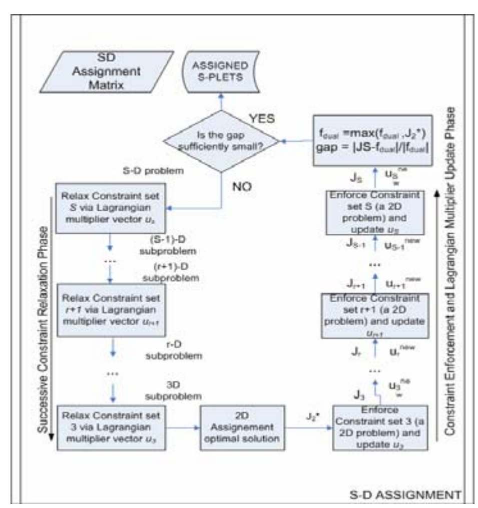

Fig. 5: Solution S-D assignment in TLF

V. Grid Based Fusion Approach

As described previously, the Grid Based Fusion Architecture has 2 levels. In this section, we describe the two levels of the architecture:

1. the fusion and extraction level where the environment is mapped and sensor data fusion is performed using occupancy grids and finally the moving objects are extracted from the grid.

2. The tracking level where the objects present in the environment are tracked using Multiple Hypothesis Tracking method [16]

A. Fusion and Extraction level

Mapping the environment and fusing sensor data using occupancy grids:

a) Probabilistic variable definitions

$Z = (Z_1,\ldots, Z_N)$ a vector of N random variables, one variable for each sensor. We consider that each sensor i can return measurements from a set Z^i.

$C_{x,y}$ in {occ, emp}. $C_{x,y}$ is the state of the bin (x,y), where (x,y) in C^2. C^2 is the set of indexes of all the cells in the monitored area.

b) Joint probabilistic distribution

The lattice of cells is a type of Markov field and many assumptions can be made about the dependencies between cells and especially adjacent cells in the lattice. In this article sensor models are used for independent cells i.e. without any dependencies, which is a strong hypothesis but very efficient in practice since all calculus could be made for each cell separately. It leads to the following expression of a joint distribution for each cell.

$$P\left(C_{x,y}, Z_1,\ldots,Z_N\right) = \frac{1}{Z} P\left(C_{x,y}\right) \times \prod_{i=1}^{N} P\left(Z_i \mid C_{x,y}\right)$$

c) Updating probability for each cell

Given a vector of sensor measurements $z=(z_1,\ldots,z_N)$, we apply the Bayes rule to derive the probability for cell (x,y) to be occupied:

$$P\left(c_{x,y} \mid z_1,\ldots,z_N\right) = \frac{P\left(c_{x,y}\right) \times \prod_{i=1}^{N} P\left(z_i \mid c_{x,y}\right)}{P(occ) \times \prod_{i=1}^{N} P\left(z_i \mid occ\right) + P(emp) \times \prod_{i=1}^{N} P\left(z_i \mid emp\right)}$$

For each sensor i, the two conditional distributions P(zi|occ) and P(zi|emp) must be specified. This is called the sensor model definition. The e-Motion group (http://emotion.inrialpes.fr) of GRAVIR Laboratory and INRIA Rhône Alpes has a strong background in building sensor models to map environment using OGs for Intelligent Transports Systems [14][15]. For each cell, the two probabilities P(occ) and P(emp) must also be specified. This is called the prior on cell occupancy.

B. Tracking level

In this part of GBF architecture, MHT method is used to solve the association problem of new extracted objects with tracks, each track corresponding to a previously known moving object. Also it permits to detect and reject spurious extracted objects (generated by sensors' noise) and to identify new moving objects incoming in the sensors' range.

The basic principle of MHT is to generate and update a set of association hypotheses. A hypothesis corresponds to a specific probable assignment of observations with tracks. By maintaining and updating several hypotheses, none irreversible association decisions are made and ambiguous cases are solved in further steps. As shown in fig. 3 (light yellow blocs), this cyclic method is composed of three different parts:

1) Objects to tracks association

A particular set of hypotheses at time k is defined by Θ_k. Knowing the set of current assignment θ_k, children of each previous hypothesis at time k-1 from Θ_{k-1} is computed to form the new set of association hypotheses Θ_k. The set of current assignment θ_k is generated considering state prediction of known objects and incoming extracted objects. The probability of each association is computed taking into account distance from each objects' prediction to incoming object.

2) Tracks management

In a second step, considering the set of computed hypotheses Θ_k, tracks are deleted, confirmed by computing estimations, or new tracks are created.

3) Filtering: compute prediction and estimation

The quality of association relies directly on the quality of filtering and especially the prediction step. Moreover, there exist several kinds of filters; the most classical is the well known Kalman filter [17]. But in all kinds of filters, the motion model (cf Fig. 3) is the main part of the prediction step. However, in the presence of uncertainties on objects' motion, defining a suitable motion model is a real difficulty. Indeed, under real world conditions, the object can have very different displacement models and it is therefore quite impossible to define a unique motion model which can match all different motions a highly maneuverable object such as pedestrian could execute. Thus it is necessary to cope with motion uncertainties in such a case.

To deal with these motion uncertainties, Interacting Multiple Models (IMM) [18] have been successfully applied in several applications [19][20]. The IMM approach overcomes the difficulty due to motion uncertainty by using more than one motion model. The principle is to assume a set of models as possible candidates of the true displacement model of the target at one time. To do so, a bank of elemental filters is run at each time, each corresponding to a specific motion model, and the final state estimation is obtained by merging the results of all elemental filters. Also, the probability the target changes of displacement model is encoded in a transition probability matrix (TPM), i.e the transition between modes which is assumed Markovian.

Nevertheless, to apply IMM on a real application a number of critical parameters have to be defined for instance the set of motion models and the transition probability matrix (TPM). To cope with this design step which can no match the reality, we define an efficient method in which the TPM is on-line adapted [21][22].

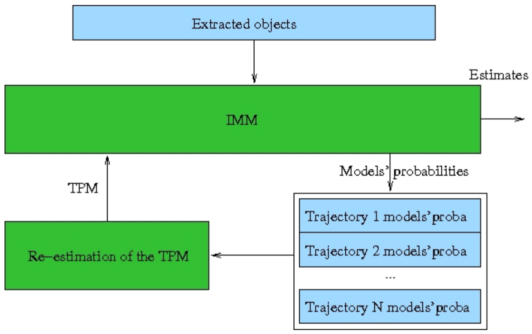

Fig. 6: Principle of TPM adaptation method

Fig. 6 illustrates the principle of our method. In this figure, software is in dark color while data are in light. To adapt the TPM in our specific situation i.e tracking moving objects, trajectories of objects are considered. Indeed, extracted objects are taken into account by set, each set corresponding to a specific object trajectory. The first observation of a trajectory is the first time the object is observed in the environment and the last one is the last observation before the object leaves the environment. While objects are tracked by the MHT and so filtering is done by IMM, each model probability is computed and stored by trajectory. When data is collected for a given number of trajectories (N in the Fig. 6), the TPM is adapted using models probabilities and is reused in the IMM for the next estimations. In this way an on-line adaptation of the TPM is obtained. Thus, the effectiveness of the MHT is improved since the prediction quality is enhanced by our method.

VI. Conclusion

In this paper a short overview of the main SDF architectures takes place with the presentation of two characteristic approaches of HLF architectures, that aim to solve the major issues observed in the past. TLF and GBF were briefly presented with a description of their modular components and the basic idea behind them. Results on their implementation would be available in the next months.

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