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Sensor Data Fusion in Automotive Applications

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1. Introduction

Sensor data fusion plays an important role in current and future vehicular active safety systems. The development of new advanced sensors is not sufficient enough without the utilisation of enhanced signal processing techniques such as the data fusion methods. A stand alone sensor cannot overcome certain physical limitations as for example the limited range and the field of view. Therefore combining information coming from different sensors broadens the area around the vehicle covered by sensors and increases the reliability of the whole system in case of sensor failure.

In general, data fusion is not something innovative in research; a lot has been done for military applications, but it is rather a new approach in the automotive field. The state-of-the-art in the automotive field is the fusion of many heterogeneous onboard sensors, e.g. radars, laserscanners, cameras, GPS devices and inertial sensors, and the use of map data coming from digital map databases.

A functional model very similar to the Joint Directors of Laboratories (JDL), which is the most prevalent in data fusion, is used in automotive fusion. According to this model the data processing is divided to the following levels: signal, object, situation and application. All these levels communicate and exchange data through a storage and system manager.

The JDL model is only a functional model which allows different architectures for fusion implementation. These architectures are divided in centralized, distributed and hybrid; each one has advantages and disadvantages.

In the data fusion process the main focus is on object and situation refinement levels, which refer to the state estimation of objects and the relations among them, correspondingly. The discrimination between these levels is also made by using the terms low and high level fusion instead of object and situation refinement.

There are several vehicular applications that fusion of data coming from many different sensors is necessary. These can be divided into three main categories: longitudinal support, lateral support and intersection safety applications.

There is a current tendency to exploit also wireless communications in vehicles. Talking cars forming ad hoc networks may be useful in future applications to cover more safety cases that can not be covered so far, due to physical limitations of onboard sensors. In this way the electronic horizon and the awareness of the driver can be extended even to some kilometres away. A lot of ongoing research is focused on the design of efficient protocols and architectures for vehicular ad hoc networks and on the standardization of this kind of vehicular communication.

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2. The revised JDL model

Sensor data fusion systems can be met in several applications, from military to civilian. Despite the wide variety of all those application domains the data fusion functional model is common and it was developed in 1985 by the U.S. Joint Directors of Laboratories (JDL) Data Fusion Group. The goal of this group was to develop a model that would help theoreticians, engineers, managers and users of data fusion techniques to have a common understanding of the fusion process and its multiple levels. Since then the model was constantly revised and updated and the one described in Fig. 1 is from the 1998 revision (Hall & Llinas, 2001).

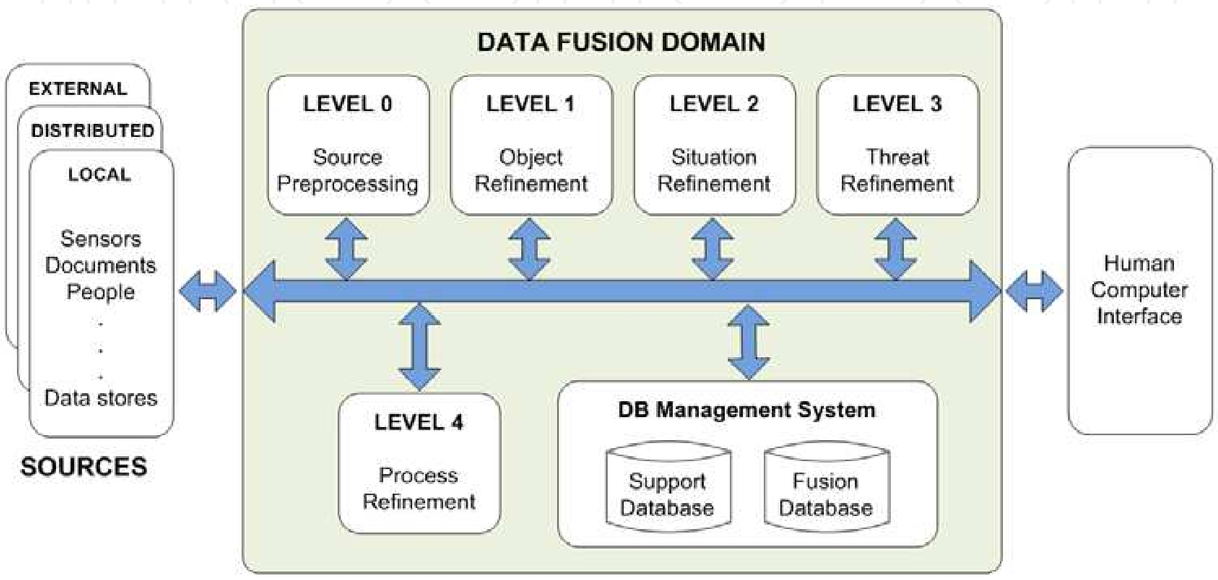

Fig. 1. Joint Directors of Laboratories (JDL) model

- *Level 0*: Preprocessing of sensor measurements (pixel/signal-level processing).
- *Level 1*: Estimation and prediction of entity states on the basis of inferences from observations.
- *Level 2*: Estimation and prediction of entity states on the basis of inferred relations among entities.
- *Level 3*: Estimation and prediction of effects on situations of planned or estimated/predicted actions by the participants.
- *Level 4*: Adaptive data acquisition and processing related to resource management and process refinement.

The question raised is how this model can be applied in multi-sensor automotive safety systems (Polychronopoulos et al., 2006). The corresponding revised JDL model is depicted in Fig. 2.

According to the automotive fusion community, level 4 does not belong to the core fusion process and hence it has been left out of the model in Fig. 2. A key topic in the automotive industry is Level 5, which corresponds to the Human Machine Interface, but it is not considered as part of the data fusion domain (see Fig. 1). While the scope of the first data fusion systems was to replace the human inference and let the system decide on its own, recently the human became more and more important in the fusion process and there are thoughts on extending the JDL model in order to include the human in the loop.

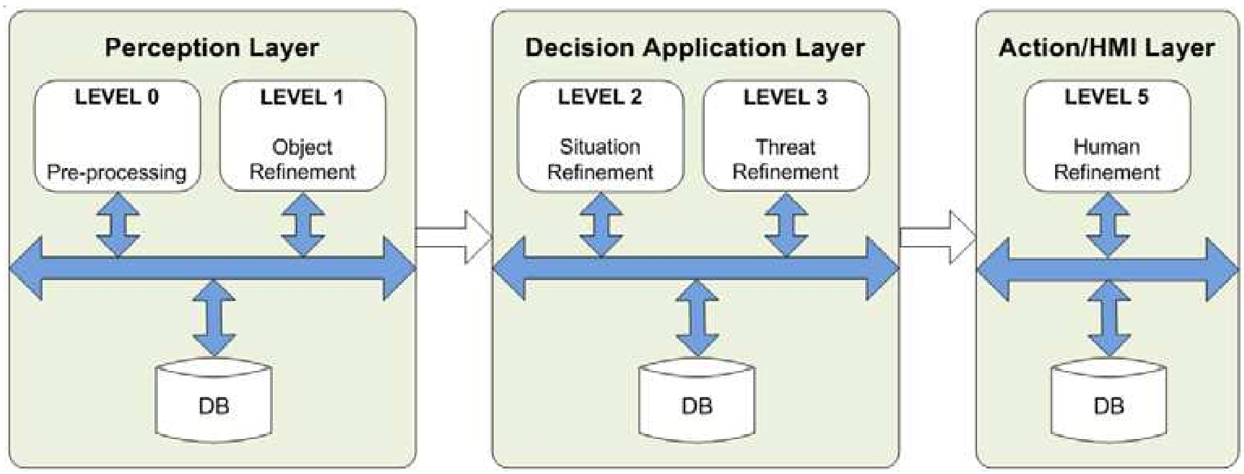

Fig. 2. Revised JDL model for automotive applications

3. Fusion architectures

The revised JDL model does not imply explicitly how the fusion process is implemented and how information among different levels is exchanged. Due to this fact a variety of architectures can be extracted from this functional model. Based on the way that information is fused, three different architectures may be implemented: centralized, distributed and hybrid. Each one has its own advantages which are mentioned in the following paragraphs and inside Table 1 (Blackman & Popoli, 1999).

3.1 Centralized architecture

This architecture is theoretically the simplest and ideally has the best performance when all the sensors are accurately aligned, that is when the sensors measure identical physical quantities. In this architecture the raw measurements from all sensors are collected in a central processing level (Fig. 3). On the one hand, this is the main advantage of the centralized architecture, that all raw data is available at the data fusion algorithm. On the other hand, the data fusion algorithm is much more complex compared to the one used in

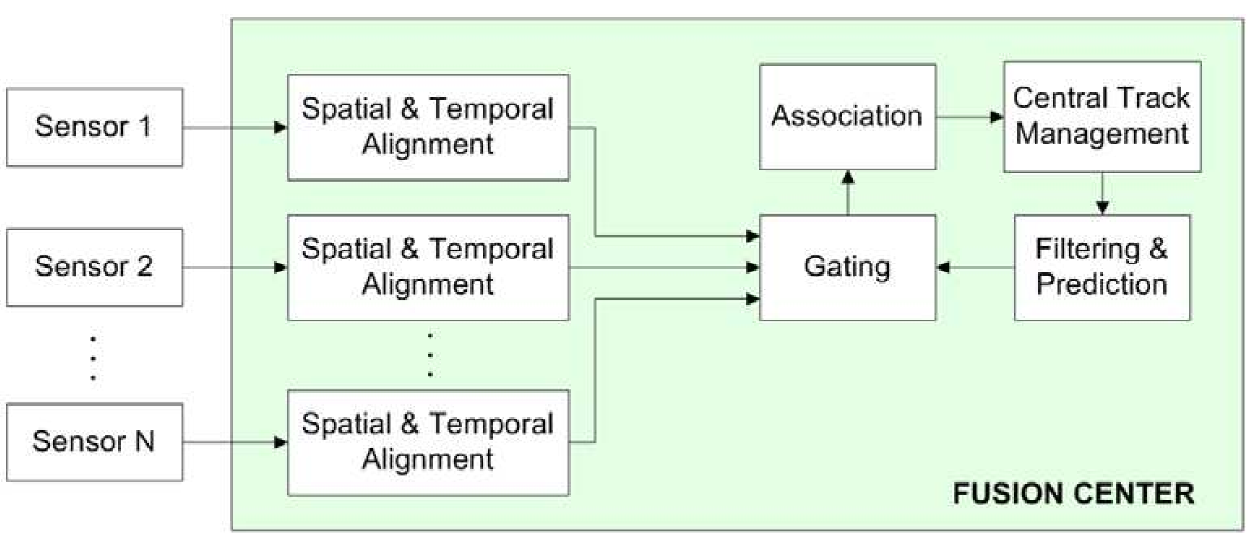

Fig. 3. Centralized Fusion Architecture

the case of distributed architecture, since it has to analyze and process raw data at a higher rate. The Multiple Hypothesis Tracking (MHT) algorithm is easily implemented since all data is available inside the central processor.
Inefficiencies in this method can occur due to the large amount of data that have to be transferred on time in the central processor.

Centralized Architecture	Distributed Architecture
• Accurate data association and tracking • Optimization of the estimated position and track of an object • Reduced weight, volume, power and productive cost with regard to distributed architecture (less processors used) • Increased HW reliability (less processors needed in the data fusion chain) • Logic and implementation are direct • Use of Multiple Hypothesis Tracking (MHT) algorithm is direct	• Pre-processing of data reduces the load in the central processor (moderate data transfer requirements) • More efficient utilization of the individual sensor characteristics • Optimization of signal processing in each sensor • Least vulnerable to sensor failure • Flexibility in the number and type of sensors used which allows addition, removal or change of sensors without significant changes in the structure of the fusion algorithm • Cost effective since it allows additional fusion in an existing multi-sensor configuration

Table 1. Advantages of centralized and distributed architecture

3.2 Distributed architecture

The distributed fusion architecture is depicted in Fig. 4. The main advantage of a decentralized architecture is the lack of sensitivity regarding the correct alignment of the sensors. Additionally, this architecture has scalable structure, avoiding centralized computational bottlenecks, is robust against sensor failure and modular.
In the case of distributed fusion pre-processed data is the input in the central processor. For each sensor the signal level processing can be carried out in the frequency domain or in the time domain or in pixel based (image processing) and the final input to the central processor will be the entity with its attributes, with a certain level of confidence for further fusion in central level. The hidden assumption made here is that the sensors are acting independently, which is not true for all the cases. Suffering from redundant information is the main drawback of this architecture.

3.3 Hybrid architecture

In hybrid architecture the centralized architecture is complemented from different signal processing algorithms for each sensor, which can provide also input to a backup sensor level data fusion algorithm (Fig. 5). The hybrid architecture keeps all the advantages of the centralized architecture and additionally allows the fusion of tracks coming from individual sensors in a sensor level fusion process. The main disadvantages of this hybrid approach are the increased complexity of the process, the potential high requirements in data transfer and the probable cross correlation between local and central trackers.

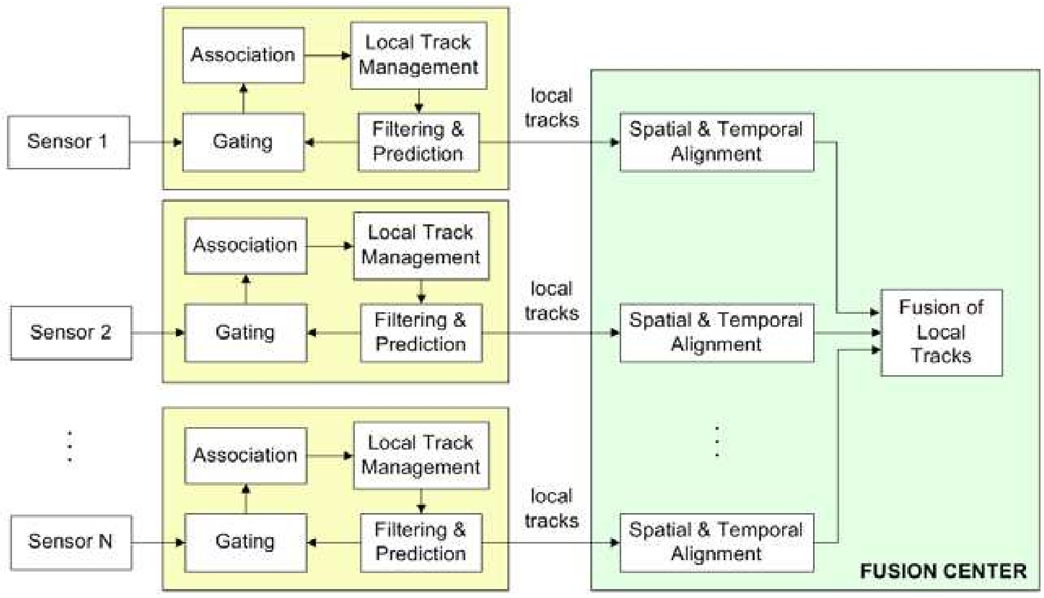

Fig. 4. Distributed Fusion Architecture

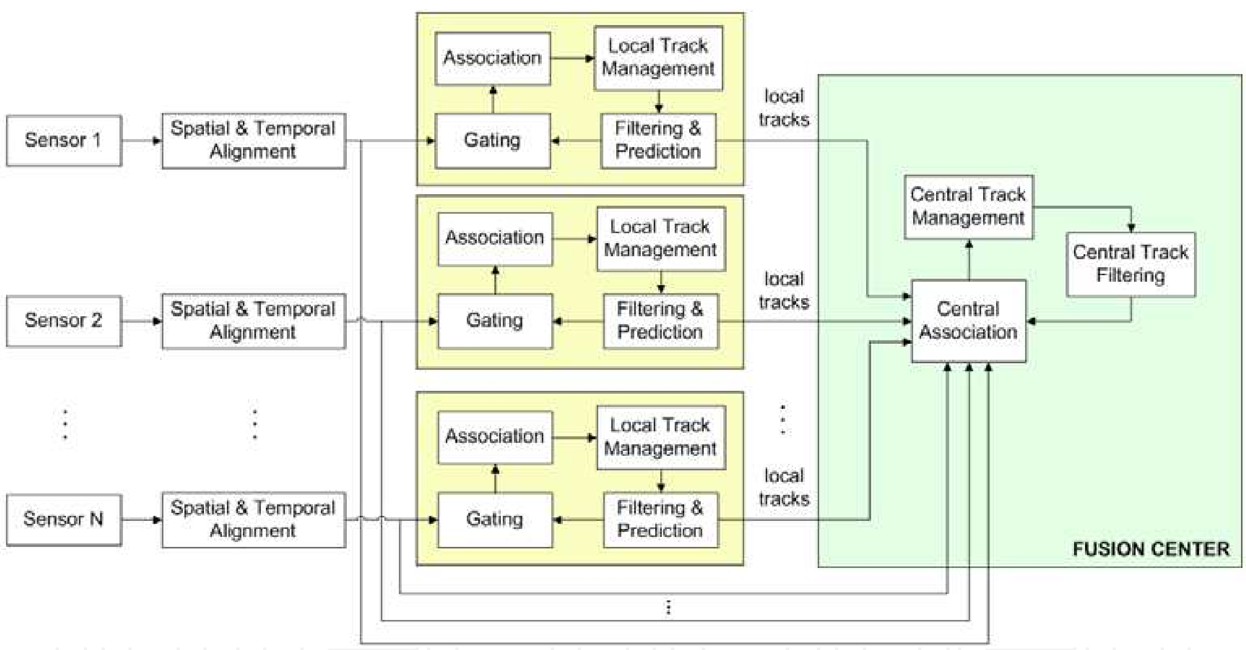

Fig. 5. Hybrid Fusion Architecture

4. Object refinement

Object refinement lies on the first level of the JDL fusion model and it concerns the estimation of the states of discrete physical objects (vehicles in our case). The analysis in this paragraph is based on the distributed architecture that was described previously. The reason for selecting the distributed approach is mainly due to its modularity and theoretically easier adaptation to different vehicles (independently of the sensors used with slight further processing). Hence, it can be considered as the most promising approach for future vehicular applications, if a level of processing is carried out inside each sensor or sensor system and no raw data is used. The main parts of object refinement are the following:

- Measurements pre-processing
- Sensor level tracking
- Spatial & temporal alignment
- Track-to-track association
- Track level fusion algorithm
- Road geometry estimation

4.1 Measurements pre-processing
Sometimes, in practical problems, when the sensors provide raw data a first step of pre-processing is required. For example, the long range radar sensors, used for automotive applications, provide object data as output, which do not need further pre-processing, while the laserscanner sensors provide polygons that need to be classified to vehicles and road borders by implementing appropriate pre-processing.

4.2 Sensor level tracking
This function corresponds to the first boxes in Fig.4, which take as input the sensor measurements. In these boxes gating, association, filtering and local track management take place. First of all, for the tracking algorithm a motion model should be selected for updating the Kalman filter (the transition matrix of the Kalman filter). The motion models that are widely used in the automotive field are the constant acceleration (CA) and the constant acceleration and turn rate model (CTRA) that are described in detail in (Bar-Shalom & Li, 1993; Blackman & Popoli, 1999).
After the selection of the motion model follows the measurement-to-track association problem that is the problem of finding the best association between tracks and measurements. Several association methods exist and the most common are the Global Nearest Neighbor (GNN) and the Joint Probabilistic Data Association (JPDA). The former is one-to-one measurement to track assignment, while the latter uses more than one measurement to update one track and more than one track can be updated by the same measurement. The selection of one of the two methods depends on the quality and nature of the sensor measurements. For instance, for a tracking algorithm carried out for a long range radar sensor, the GNN approach is adequate (Blackman & Popoli, 1999; Floudas et al., 2007).
Then, according to the results of the association problem, the track management module should decide for initialization of new tracks and confirmation or deletion of existing tracks. The decision process is based on simple rules of consecutive "hits" and "misses", where a hit is defined when there is a successful association between at least one measurement and a track and a miss when a track remains without an assigned measurement for this cycle of the process (Floudas et al., 2008).
The final step in sensor level tracking is the filtering and prediction function, where the new tentative tracks (unassigned measurements) and the previously existing confirmed tracks are filtered and outputted to the track-to-track association procedure. Also according to the selected motion model the future position of the updated tracks (new and existing) is predicted and the gate for further track processing is calculated. The scope of this gate is to reduce the computational load of checking all measurements with all tracks and just investigate the association of the tracks with measurements that fall inside their gates.

4.3 Spatial & temporal alignment

The next step, right after the sensor level tracking, is the spatial and temporal alignment of all the tracks that are coming from the different sensors. For further association and fusion of these tracks a common coordinate system and time reference are needed. In most cases the coordinate system that is used has its origin in the geometrical center of the vehicle and the longitudinal axis is the x-axis. As a time reference the time provided by the Controller Area Network (CAN) bus is used. CAN is actually a network protocol, designed specifically for automotive applications, that allows communication among the electronic control unit(s) of each vehicle with other devices and sensors connected to it. All tracks that are coming from different sensors are fed into the CAN bus and in this way time synchronization is accomplished.

4.4 Track-to-track association

After the tracks that are coming from the sensor level tracking have been aligned in space and time, the track-to-track association is executed. The aim of the association is to decide which tracks that are coming from different sensors correspond to the same object. This is useful in cases that we have multiple sensors with common or complementary areas of surveillance. The multidimensional assignment approach is used in case that three or more sensors are observing the same object. For this kind of problems the Lagrangian relaxation method is directly applicable (Deb et al., 1997).

4.5 Track level fusion algorithm

There are several methods to update two or more tracks (using state vectors and covariance matrices) with track-to-track fusion; some of them are summarized in the following lines.
Regarding the selection of fusion method for two tracks update several methods are applicable; starting from Simple Fusion (Singer & Kanyuck, 1971) that implies that the tracks are uncorrelated thus it is a suboptimal method. The Weighted Covariance Fusion (Bar-Shalom, 1981; Blackman & Popoli, 1999) accounts for correlation between trackers (common process noise) producing the cross covariance matrix from the existing covariance matrices.
The fusion finally selected when reliable tracks are available is the Covariance Intersection method (Uhlmann, 1995). Covariance Intersection method deals with the problem of invalid incorporation of redundant information.
The Covariance Union method (Uhlmann, 2003) solves the problem of information corruption from spurious estimates. Covariance Union method guarantees consistency as long as both the system and the measurement estimates are consistent, but it is computationally demanding. Covariance intersection method is a conservative solution but superior to weighted covariance method.
However in many practical cases the covariance of obviously not reliable tracks can lead to inaccurate estimates, and therefore a constant predefined weight can be used for these cases.
Finally, according to the road environment, the computational load, the process noise, the correlation of sensor measurements and the independency assumption, the proper method for fusion can be selected.

4.6 Road geometry estimation

The role of object refinement is not only to estimate the state of each vehicle, but also to estimate the status of other objects in the road environment such as the road borders. Parallel to sensor level tracking a road geometry estimation algorithm is running. The mathematical model for the road geometry representation could be either the clothoid (Lamm et al., 1999) or the B-Splines (Piegl & Tiller, 1996) model. The basic sensor used for extracting the road geometry is a camera. This camera, after image processing, provides information about the lanes, the lane markings, the curvature of the road etc. and utilizing the clothoid or the B-Splines model a first estimation of the road geometry is calculated.

Moreover, the road geometry is estimated based on information coming from a digital map database. The current position of the vehicle in the map is extracted based on a GPS or a differential GPS sensor and advanced map matching techniques. A way of extracting the road geometry using digital maps is described in detail by (Tsogas et al., 2008a).

The fusion of these estimations to obtain the final road geometry estimation is carried out using a fuzzy system (Jang et al., 1997) or a Dempster-Shafer (Dempster, 1968; Shafer, 1976) reasoning system. Additionally, other active sensors, e.g. radars or laserscanners, can be used as input to the fusion process to increase the robustness of the system (Polychronopoulos et al., 2007; Tsogas et al., 2008a). The fusion process is based on the assumption that camera and laserscanner data is more reliable close to the vehicle, while map data is more accurate far ahead from the vehicle.

5. Situation refinement

Situation refinement belongs to the second level of the JDL model and it refers to the relations among the various objects in the road environment. Quite often the term high level fusion is used instead. Within situation refinement the meaning of the current situation around the vehicle is tried to be comprehended. Some questions that are dealt with here are: 'Is this group of slow moving vehicles involved in a traffic jam?', 'Are the trajectories of two vehicles approaching each other intersecting? Is there a danger of collision?' and so on.

The three most known theories that are used in high level fusion, proportional to the problem, are: Fuzzy systems (Dubois & Prade, 1980; Jang et al., 1997), Bayesian probability theory (Bernardo & Smith, 2000; Bolstad, 2007) and Dempster-Shafer theory (Dempster, 1968; Shafer, 1976). In this chapter, an overview of the main parts of situation refinement will be outlined, but the selection of the most appropriate theory is not explicitly indicated.

The outcome of situation refinement enriches the environment model including additional attributes of the ego-vehicle and other objects (e.g. predicted paths, detected maneuvers).

Summarizing, it can be said that situation refinement is the basis to assess the risk of present and predicted future situations, given that all involved participants act in a predictable way.

Finally, situation refinement can be uncertain due to incompleteness of knowledge and uncertain information sources (Tsogas et al., 2007; Tsogas et al., 2008b).

The main parts of situation refinement discussed here, are the following:

- Path prediction
- Maneuver detection
- Driver intention
- Assignment of a lane to an object
- High level events

5.1 Path prediction

Path prediction is a key component of situation refinement and it can be divided into three parts. The first part is to calculate the future path of the vehicle based on its current dynamical state and the adoption of a specific motion model. This model could be the Constant Velocity (CV), Constant Acceleration (CA), Constant Turn Rate (CTR) Constant Turn Rate and Acceleration (CTRA) or Bicycle Model (BM) (Liu & Peng, 1996; Pacejka, 2006), a combination of two or three of these models with the use of an Interacting Multiple Model (IMM) filter or a dynamically adaptive rule-based model. A Kalman Filter is also useful for smoothing the vehicle's dynamics (e.g. speed, yaw rate) and reducing the measurement noise. The second part consists of the extraction of the future path based on the estimation of the road borders and assuming that the driver will follow the road geometry without performing any maneuver. Moreover in this part a dedicated motion model is required. Almost always a CV model suffices. The third and more sophisticated part is the combination of the first two parts. The fusion of these paths can be performed in several different ways. The simplest way is to use a weighted average estimation. For the calculation of the short term future path the dynamic state of the vehicle is more important, while for the long term path the estimation of the road geometry has major influence. Significant work on this issue has been carried out by (Polychronopoulos et al., 2007).

5.2 Maneuver detection

The purpose of this algorithm is to identify the maneuver performed by the driver. This calculation can be realized with a Dempster-Shafer reasoning system. At the beginning the set of the maneuvers that the system can detect should be formed. An example set is the following:

$$\Omega=\{\text{free motion, lane change, overtaking, following another vehicle}\}$$

According to the above set and the information sources, the Dempster-Shafer reasoning system can estimate the actual maneuver that is performed by the vehicle. The information sources could be: the estimated time that the vehicle will cross the lane, the minimum distance of the vehicle to the lane marking, the time in which this minimum distance will be achieved, the curvature of the road, the curvature of the vehicle's path and the distance from the vehicle in front. For each one of these sources a basic probability assignment function will be assigned for calculating the evidence masses. Then the fused evidence masses will be calculated and the belief and plausibility values will be extracted in order to evaluate the final confidence.

Here is an example, how the algorithm calculates the performed maneuver: First of all let's assume that the ego vehicle is overtaking another vehicle. The time to cross the lane should have very small values and the ego vehicle should be following another vehicle in relatively small distance. If this is the input information to the system, then the algorithm should detect an overtaking maneuver with high confidence.

5.3 Driver intention

Another important function in the situation refinement domain is checking whether the maneuver performed by the driver was intended or not. This can be of great importance especially for the Human Machine Interface (HMI) application. For example, if the output of the driver intention module is that the current performed maneuver is not intended, then there is a high possibility of an upcoming unpleasant situation, so the HMI system should intervene and inform the driver before it is too late. A Dempster-Shafer or Rule based or Fuzzy inference system can be used for identifying the driver's intention. The input sources

to this system comprise the output of maneuver detection algorithm, the type of the road (rural, highway, construction area etc.), the curvature of the road, and other vehicle data such as the status of the indicator (ON/OFF), the velocity etc.
The formulation of the rules in a rule based system or the membership functions in a Fuzzy inference system or the basic probability assignment functions in a Dempster-Shafer system are based on simple guidelines. For instance, the possibility for intended lane change in sharp-curved road segments is lower than in cases of straight road segments. When the curvature exceeds a threshold then it is very unlikely that the driver will change lane.

5.4 Assignment of a lane to an object

This part of situation refinement is responsible for assigning a lane index to every fused object relative to the future path of the ego vehicle. It indicates the relationship among the detected objects in the road, the lanes of the road and the ego vehicle. A Dempster-Shafer reasoning system is applicable also in this case.
The sources that can be used to estimate the assigned lane index to the object are the following:

- offset of the position of each vehicle from the position of the ego vehicle exploiting the future path calculated previously using different motion models (CA, CTR & CTRA)
- distance of the detected object from the ego vehicle

The offset is calculated using the future trajectory of the ego vehicle and the coordinates of the detected object.
The basic probability assignment functions are formulated based on the following rules:

- The closer the detected object is located to the lane borders, the lower evidence mass is assigned to the corresponding proposition.
- The further the detected object is, the lower the evidence mass assigned to the corresponding information source is.

5.5 High level events

Since situation refinement is also called high level fusion, high level events such as estimation of weather conditions and traffic, should be taken into account within this fusion level. Both the estimation of the traffic density and of the weather conditions could be based on a Bayesian network approach (Jensen & Nielsen, 2007; Korb & Nicholson, 2004).
As far as the traffic is concerned, it could be classified in light, medium or dense traffic. For this calculation the fused objects from object refinement as well as the road attributes such as lane markings, road offset, lane offset, road width, lane width and heading, curvature and curvature rate of the corresponding segment are needed.
The estimation of the weather conditions (fog, rain, icy road) is much more complex, because for this kind of calculations, input from specific sensors is needed.

6. Application and use cases

In the automotive field there are several applications that fusion of data of various sensors is necessary. For all around coverage and for supporting at the same time a lot of different applications, data fusion becomes a complicated procedure. The sensors used are very heterogeneous and vary in quality. Some sensors are of poor quality, others, like the long range radars, are of high quality but due to their limited field of view support from other sensors with wider coverage area is necessary. The synchronization of all these sensors, the processing power needed (many embedded PCs), the space they need for installation in the car and the cost comprise constraints for the fast incorporation of such systems in the market. Despite all the above facts, the key challenge in all these applications which would lead the future active safety systems in success is a robust and reliable data fusion.

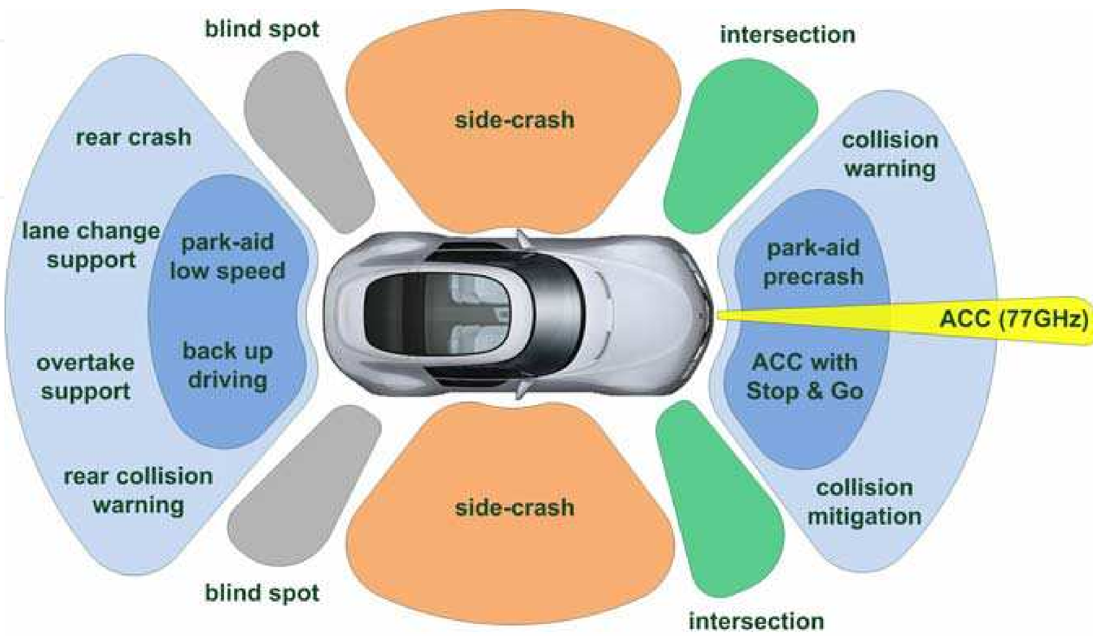

Fig. 6. Coverage areas for various automotive safety applications

The figure above shows many different automotive safety applications and their coverage areas. It is obvious that there is a significant variety of applications in the automotive field, such as Adaptive Cruise Control (ACC), front/rear collision mitigation, parking aid, front/rear collision avoidance, blind spot support, lane change and lane keeping support, vulnerable road users (e.g. pedestrians, cyclists) protection and so on.

The aim of this chapter is not to refer to all these applications but to highlight the most important ones and these that will contribute to the reduction of road accidents and respectively to the fatalities.

6.1 Intersection safety

Intersections comprise a major accident hotspot according to statistics, as proved by the data taken out of CARE2005 and provided by Renault. Above 40% of all injury accidents in Europe take place at intersections, while approximately 25% and 35% of the fatalities and the serious injuries come out from intersections respectively. The aim of intersection safety applications is to assist and protect not only the drivers, but also the vulnerable road users (e.g. pedestrians, cyclists). Accident scenarios at intersections are amongst the most complicated, since intersections are frequented by many and different road users approaching from different directions. Some examples of accident scenarios are the following:

- Collisions with oncoming/crossing traffic while turning into or crossing over an intersection
- Violation of the traffic light (red light runner)

For this type of applications advanced on-board sensor systems are necessary, but even such sensors maybe don't suffice. The exploitation of wireless cooperation among the road users and especially infrastructure support at intersections is more than essential. In this paragraph the analysis will be restricted on the in-vehicle systems.
An example of an equipped vehicle with advanced on-board sensors for intersection scenarios is depicted in Fig. 7.

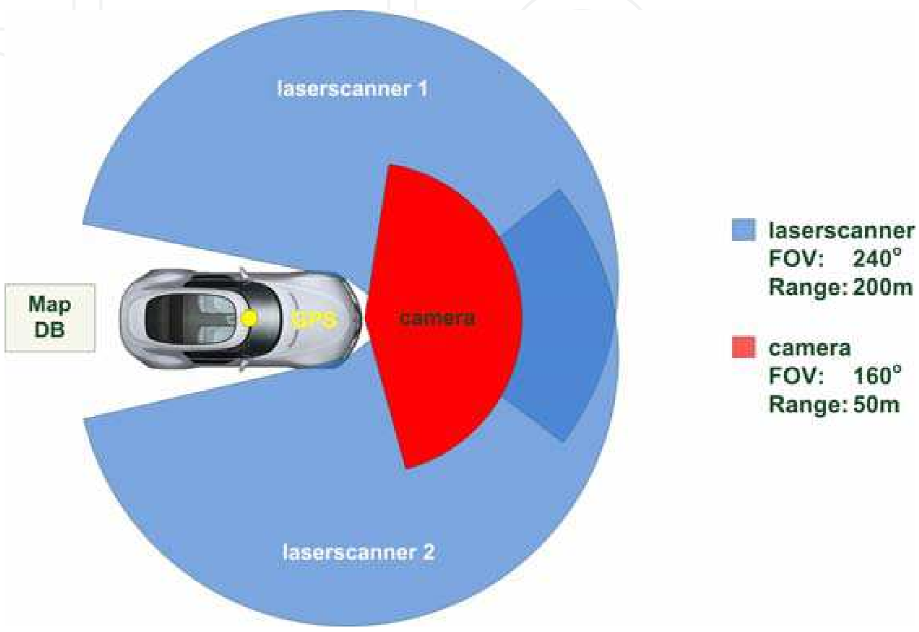

Fig. 7. Equipped vehicle for intersection safety applications

The key factors at intersection are the use of sensors with wide field of view, like the laserscanners, and highly accurate vehicle localisation. The laserscanner can detect other vehicles, pedestrians, cyclists and natural landmarks. The camera, after image processing, can extract information about the lane markings. Highly accurate vehicle localisation can be performed by fusing information from camera, laserscanner and map data extracted from a detailed map of the intersection with the use of a GPS/DGPS sensor.

6.2 Safe speed and safe distance

This application belongs to the more general category of longitudinal support systems, which comprise Adaptive Cruise Control (ACC), front/rear collision avoidance, stop and go etc. At this point it should be mentioned that ACC systems were the first systems introduced to a vehicle, which made use of a long range radar sensor. The aim of ACC was to automatically adjust the vehicle's speed and distance from the vehicle ahead. Safe speed and safe distance application is an extension of the traditional ACC system.
In Europe numerous car accidents happen due to inappropriate vehicle's speed or headway. According to European Transport Safety Council, more than 40% of fatal accidents are caused by excessive or inappropriate speed. The higher impact speed the greater likelihood of serious and fatal injury. In addition, rear-end and chain accidents represent a significant part of road accidents in Europe as well.
The aim of a safe speed and safe distance application is to aid the driver in avoiding accidents related to excessive speed or too short headway. Specifically, the sensorial suite of

such a system consists of a long range radar and two medium range radars for obstacle detection, a vision-based system for lane detection and a combination of differential GPS and digital map data for global positioning.
Figure 8 highlights an equipped vehicle for safe speed and safe distance applications.

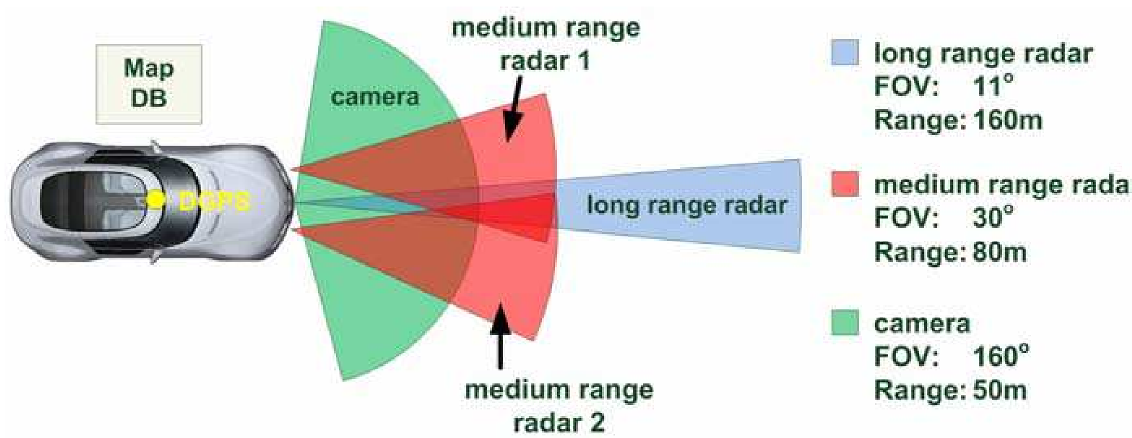

Fig. 8. Equipped vehicle for safe speed and safe distance applications

Data fusion takes place at multiple levels in order to provide an enhanced view of the environment. Differential GPS and inertial sensors are fused together with map data for acquiring a more accurate positioning. Data from the radars is fused and a more complete representation of the environment is achieved. Also for this application the predicted paths of the host vehicle and other vehicles play a key role.

6.3 Lane keeping support

Lane keeping support may be considered as a member of the lateral safety applications family. This category comprises also other important applications such as lane change assistance, lateral collision avoidance and lane departure warning. The aim of lane keeping support systems is to assist the driver to keep the vehicle safely in its own lane. For this reason vision-based sensing systems are utilized, which observe the curvature of the road and the position of the vehicle in the lane. In contrast to other warning safety systems, the lane keeping support system utilizes an actuator, which applies a vibration to the steering wheel in order to keep the host vehicle in the lane.
The objective of lane keeping support systems is not to control the vehicle completely automatically, but mainly to give the driver an intuitive support by turning the steering wheel in the right direction. However, the driver has to react and take control of the vehicle so as to avoid lane departure.
If the system detects a lane departure, it issues a warning to the driver and at the same time it activates the steering actuator. This approach exploits data fusion between camera, digital maps and other active sensors like radars or laserscanners. The fact that the system comprises an actuator means that the system is a hard real-time system. This in turn poses tight requirements on the performance of the data fusion algorithms. The figure below shows an equipped vehicle that supports lane keeping applications.

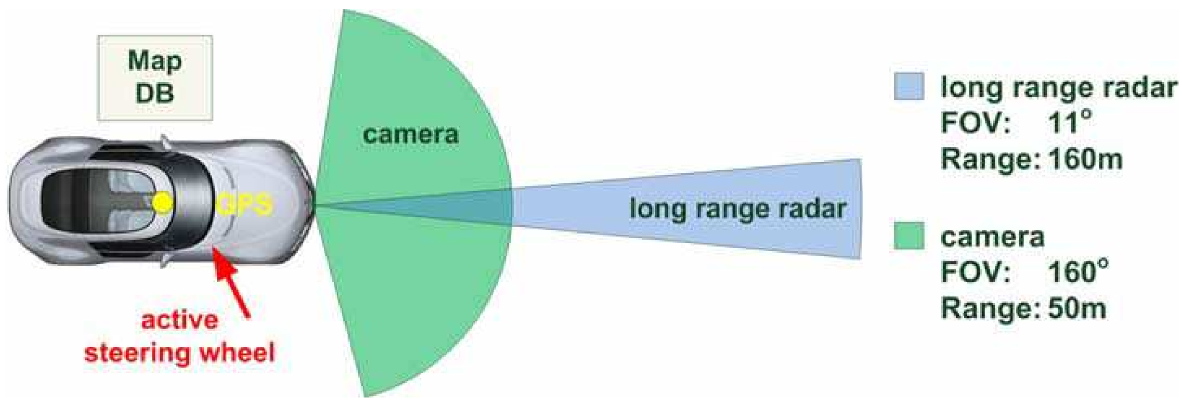

Fig. 9. Equipped vehicle for lane keeping support applications

7. Future trends

In the past decade the advances in autonomous sensor technologies and the major objective of the European Union to reduce to a half road accidents and fatalities by 2010, led to the development of advanced driver assistance systems. The fusion of data coming from different advanced in-vehicle sensors was initially in the centre of this attempt. However, this approach suffers from serious limitations. Specifically:

- the perception environment of the vehicle cannot go beyond the sensing range
- the sensor systems cannot perform well in all environments (the urban roads comprise a major challenge)
- in several cases the system is not able to perceive the situation in time in order to warn the driver and suggest a corrective action
- the cost of the sensor systems is too high and so their installation is feasible only at luxurious vehicles.

However, recently there is a lot ongoing research on cooperative vehicles, which focuses on overcoming all the above limitations. There are two different types of communication: roadside-to-vehicle and vehicle-to-vehicle, as pointed out by CAR 2 CAR communication Consortium (Fig. 10). In addition, the exploitation of wireless communications in vehicular environments will enhance and expand currently available safety and comfort applications (e.g. tunnel support, upgrade of intersection safety, internet in the vehicle, ecological driving). A cooperative collision warning application is presented in detail by (Lytrivis et al., 2008).

The limited bandwidth, security issues, privacy, reliability and propagation are some of the emerging disadvantages of the wireless connectivity in vehicles. For all the above reasons new organizations, initiatives and working groups, such as DSRC, WAVE, C2C-CC, were created.

Dedicated Short Range Communications (DSRC) is a short to medium range (1000 meters) communications service that supports both public safety and private operations in roadside-to-vehicle and vehicle-to-vehicle communication environments by providing very high data transfer rates. It operates at 5.9 GHz and provides a spectrum of 75 MHz.

The design of an effective communication protocol that deals with privacy, security, multi-channel propagation and management of resources is a challenging task that is currently under intensive scientific research. A dedicated working group has been assigned this specific task by IEEE and the ongoing protocol suite is the IEEE 1609, mostly known as WAVE (Wireless Access in Vehicular Environments).
The CAR 2 CAR Communication Consortium (C2C-CC) is a non-profit organization initiated by European vehicle manufacturers, which is open for suppliers, research organizations and other partners. The goal of the C2C-CC is to standardize interfaces and protocols of wireless communications between vehicles and their environment in order to make the vehicles of different manufacturers interoperable and also enable them to communicate with road-side units.

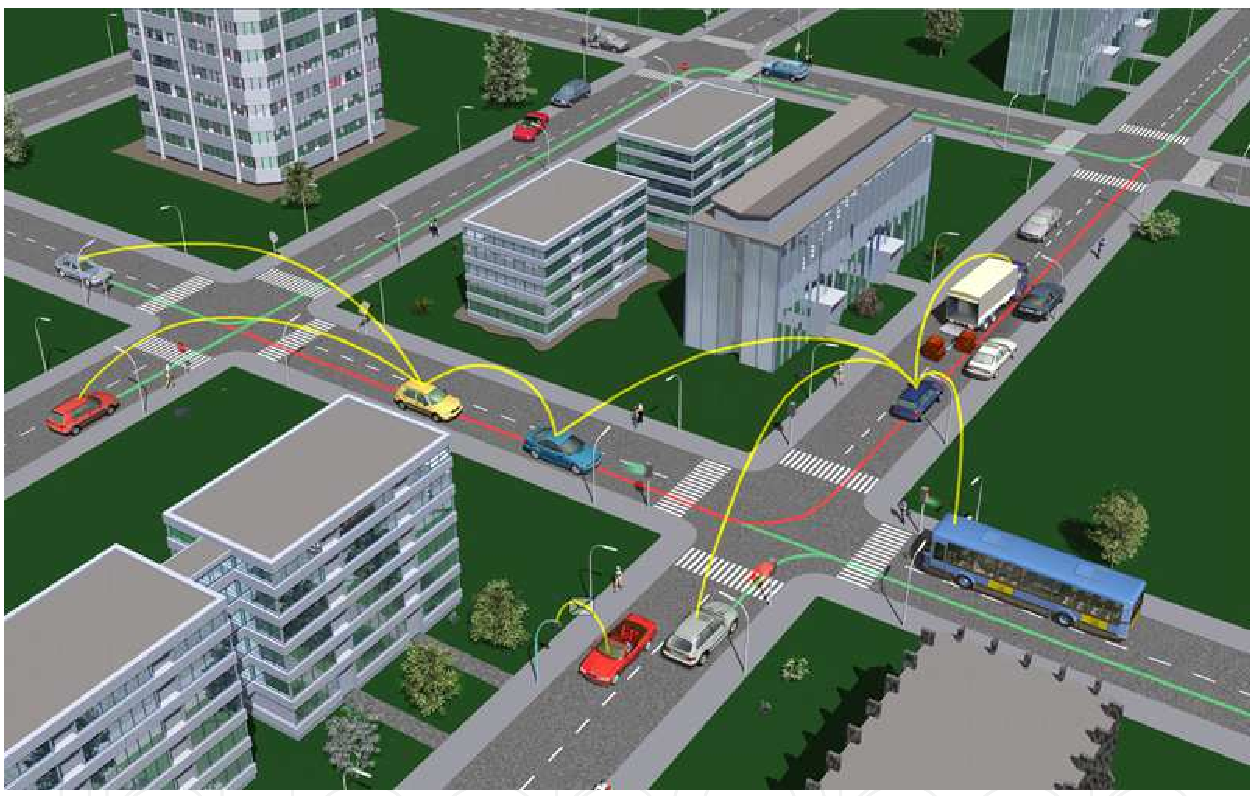

Fig. 10. Vehicles cooperating with other vehicles and roadside units (http://www.car-to-car.org/index.php?id=131)

Additionally, new challenges are posed to the data fusion process. The association and synchronization of data from on-board sensors together with the wireless network data is the main challenge. Moreover, the manipulation of delayed information and the reliability of the information transferred via the network are other important issues.

8. Conclusion

This chapter has summarized the state-of-the-art in sensor data fusion for automotive applications, showing that this is a relatively new discipline in the automotive research area, compared to signal processing, image processing or radar processing. Thus, there is a tendency of using already available knowledge from other research areas, such as the military or robotic areas. The initial and the revised JDL functional fusion model, applicable for automotive industry, have been highlighted. Several discrete architectures were described. On the one hand, it can be stated that central fusion architecture, which uses more sensor data at the processing level, is able to deliver the higher performance. On the other hand, the processing demands and the integration effort are much more significant compared to the distributed fusion architecture. Moreover the two main levels of fusion, object and situation refinement, and their corresponding functions were outlined. Additionally, some automotive applications which make use of data fusion were described. Finally, a brief report about the current research activity and the new challenges derived from the exploitation of wireless communications were indicated.

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Data fusion is a research area that is growing rapidly due to the fact that it provides means for combining pieces of information coming from different sources/sensors, resulting in ameliorated overall system performance (improved decision making, increased detection capabilities, diminished number of false alarms, improved reliability in various situations at hand) with respect to separate sensors/sources. Different data fusion methods have been developed in order to optimize the overall system output in a variety of applications for which data fusion might be useful: security (humanitarian, military), medical diagnosis, environmental monitoring, remote sensing, robotics, etc.