

Sensor Data Fusion for Active Safety Systems

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ABSTRACT

Active safety systems will have a great impact in the next generation of vehicles. This is partly originated by the increasing consumer's interest for safety and partly by new traffic safety laws. Control actions in the vehicle are based on an extensive environment model which contains information about relevant objects in vehicle surroundings. Sensor data fusion integrates measurements from different surround sensors into this environment model. In order to avoid system malfunctions, high reliability in the interpretation of the situation, and therefore in the environment model, is essential. Hence, the main idea of data fusion is to make use of the advantages of using multiple sensors and different technologies in order to fulfill these requirements, which are especially high due to autonomous interventions in vehicle dynamics (e. g. automatic emergency braking). The technical challenge in the development of a serial product relies in the implementation with given sensors, as well as in the risk assessment of the system.

INTRODUCTION

In front impacts, automatic emergency brake systems reduce vehicle velocity to minimize accident damages. In a critical situation, the use of a warning signal allows the driver to react before activation of the automatic brake. If the driver does not react after the warning signal, the automatic brake is activated [2, 3]. Due to this autonomous intervention in vehicle dynamics, requirements in terms of reliability and accuracy in the information about the vehicle surroundings are very high.

At low speed approaches, and depending whether the driver is attentive or not, the optimal warning time point may differ. In case of inattention, the warning signal has to come early enough so that sufficient reaction time is given to the driver. However, attentive drivers wait normally until latest possibility for convenient braking. The braking time point in this case is usually after the warning signal - provided at time point appropriated for inattentive drivers, and therefore attentive drivers might be disturbed with warning signals.

Another type of dilemma arises because the degree of danger can be deescalated either by braking or by evading the object. Especially in approaches at high speed, the object distance for collision avoidance by braking is longer than for object evasion. Thus, convenient evasion of the object is still possible at the time point for avoiding the collision by brake activation. Therefore, knowledge whether to evade the object is possible becomes crucial for solving this second dilemma. Hence, in addition to vehicles in the same lane, to take parallel traffic into account is of great advantage.

With relation to accident statistics, [Figure 1](#) illustrates the main collision types within the field of effect of automatic brake systems for cars and similar vehicles, like pick-ups or vans. From this figure, a system that takes front traffic into account, may contribute to reduce damages in about 27% of all accidents.

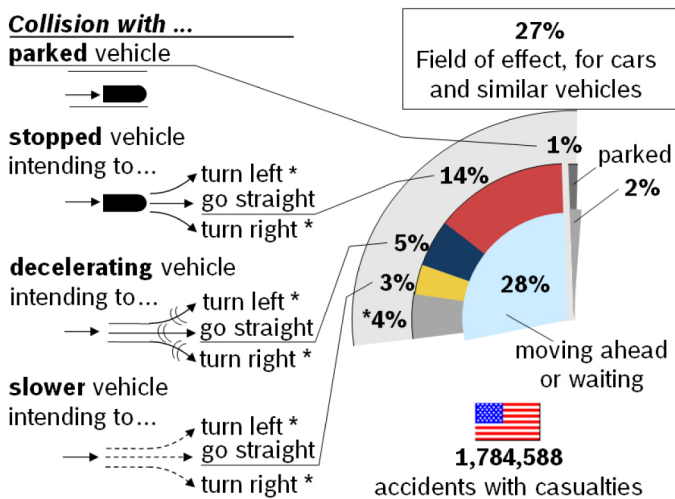


Figure 1. Accident statistics. Field of effect of collision avoidance braking systems for cars and similar vehicles, like pick-ups or vans. Sources: StBA, GIDAS, GES, NHTSA, Year 2006.

Requirements for the prototype system described in next sections have been derived systematically top-down from function to data fusion, and from data fusion to sensors. Required quality in detection and object data has been established for frontal collisions, in which the own, and right and left parallel lanes are occupied by stopped vehicles.

CONCEPTUAL ISSUES

Modeling of vehicle surroundings addresses the representation of relevant data (referred as *environment model* or *surround model* or *data model*) and processing of sensor measurements. For an automatic emergency brake system, the data model represents processed sensor information, which is provided to the next processing step, the *situation interpretation*, for risk assessment of the traffic situation (e.g. position of collision relevant objects relative to own vehicle and its uncertainty, calculated from distance measurements, and represented by a state vector with mean and variance values).

DATA MODELS

The environment model represents data about objects in vehicle surroundings expressed by probabilities and their density functions. The main factors to consider in the selection of the model are: the class of relevant objects, type of information about them, degree of detail of probability density functions and processing algorithms.

One possible choice is to model an object relying on a parameterized *single best estimate*, which is inferred from sensor data. This estimate is summarized in a state vector - expected to have a relatively low number of components per object. The components of the state vector describe, for

example, position, dynamics and their uncertainties of objects in vehicle surroundings. Uncertainties are commonly approximated by Gaussian distributions due to the low number of necessary parameters as well as low required processing complexity.

However, in this case, model accuracy and certainty depend on the degree of matching of the real densities with Gaussian (see [5, 6]).

An alternative to the single best estimate approach is to approximate probabilities and density functions by a finite number of values, each roughly corresponding to a space in the data model. Some methods, like *grid-based*, decompose model space in cells, which contain the cumulative probability of density functions. Other methods, approximate density functions by finitely many samples called *particles*. No strong parametric assumptions are made, and therefore these methods are able to cope with varying and very different density functions. The number of parameters to approximate densities is variable, and the quality of approximations depends on it. As the number of parameters increase, these methods converge to the true density. Nevertheless, the computational complexity becomes usually, for that reason, a critical issue (see also [6]).

For reduction of the amount of data, grid cells or particles can be clustered into polygons. Polygon periphery is defined with vertices and edges, which results in a *polygon-based* data model. Thus, for example, one polygon would correspond to a certain space of the data model with cumulative probability higher than a certain threshold. However, in order to achieve a significant data reduction, the number of vertices must be lowest possible, while keeping the model accuracy sufficiently high. As for grid and particles, computational complexity can be a critical aspect, if no significant data reduction is achieved.

DATA PROCESSING

Processing of sensor data is necessary, since measurements are usually corrupted by noise and limited by factors like resolution. Furthermore, if all necessary object quantities are not provided, inference of non-measured quantities becomes necessary. *Object hypothesis* is a term that will be used to refer processed sets of sensing data produced by the same object and assumptions about its motion.

Selection of data processing algorithms depends on the data model used. Examples of references are: [5] with different methods for the single best estimate data model, and [6] for grid- and particle-based data models.

fusion levels

In the development of sensor data fusion, a major conceptual aspect is the selection of the level at which the information

from the different sensors is processed. The main choices are *feature level* and *object level*. Figure 2 illustrates the main signal processing steps from sensors to situation interpretation, and fusion levels.

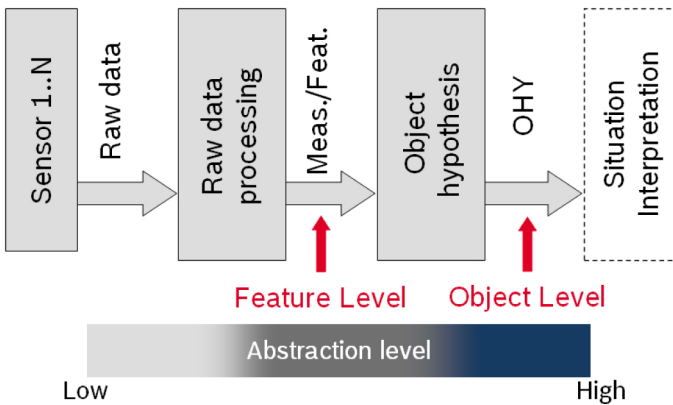


Figure 2. Main levels for sensor data fusion. OHY: Object hypotheses.

Sensor data fusion at feature level processes all available data at the same place. Object hypotheses are generated from measurements and features provided by all sensors. For example, radar locations (distance and angle measurements) are processed together with disparities from stereo-video. At this level, the difficulties that a certain sensor might have for initiating object hypotheses are supported by information from other sensors.

By the alternative sensor data fusion at object level, each single sensor generates object hypotheses based on its own measurements. For example, object position¹ is computed independently by radar and by stereo-video from locations and disparities respectively; data fusion integrates object position from each sensor into a fused object position. An advantage of this level is that algorithms can be optimized for a single sensor technology, and degradation of single sensor information does not affect to other sensors.

centralized and decentralized algorithm architectures

Depending on the fusion level, there are two basic algorithm architectures: centralized and decentralized for data fusion at feature level and object level respectively.

Figure 3 illustrates the centralized architecture. In this architecture, fused object hypotheses are computed by using early processed sensor raw data, i.e. measurements and/or features, from all sensors.

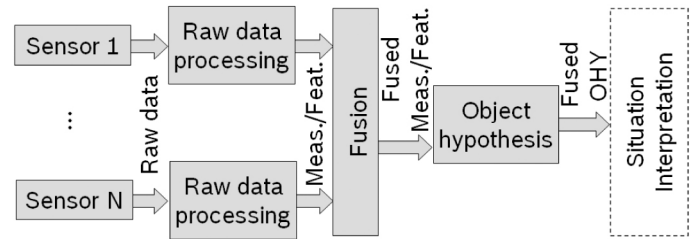


Figure 3. Centralized architecture. OHY: Object hypotheses.

Figure 4 illustrates the decentralized architecture. In this architecture, early processed sensor raw data is used to initiate and update single sensor object hypotheses. In the fusion step, fused object hypotheses are computed from single sensor object hypotheses.

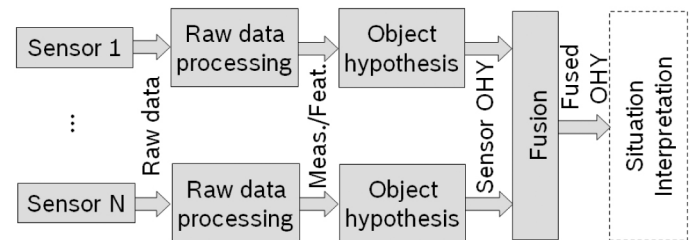


Figure 4. Decentralized architecture. OHY: Object hypotheses.

PROTOTYPE WITH AUTOMATIC EMERGENCY BRAKE SYSTEM

Within the framework of the public funded project AKTIV [7], a vehicle prototype has been equipped with environment sensors, electromechanical components for automatic brake activations and computer resources for data processing.

SENSING SYSTEM

After deriving requirements from data fusion to the sensing system, the combination of Long Range Radar and stereo-video was selected to deal with frontal collisions. Radar provided measurements about longitudinal position and dynamics, and position in lateral direction. Video provided data of position and dynamics in longitudinal and lateral directions, as well as object dimensions (width and length). Figure 5 illustrates these sensors.

¹Note that this is a subspace of the object hypothesis