

# Sensor Fusion as an Enabling Technology for Safety-critical Driver Assistance Systems

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## ABSTRACT

Driver assistance systems are incorporating more and more advanced safety functions. As these functions have to react quickly and reliably in emergency situations with a false alarm rate close to zero a high integrity of the environmental perception is required. This elevated level of signal integrity can be achieved by data fusion, where the information of several, in general heterogeneous sensors is combined to obtain a better model of the environment in terms of accuracy, object integrity, object identity, etc. As an example, we demonstrate the power of sensor fusion by an automatic emergency brake (AEB) system whose environmental perception is based upon a video camera and a radar sensor. In particular we discuss the improvement of kinematic attributes such as object lateral distance as well as the object's confidence or probability of existence.

## INTRODUCTION

Automotive driver assistance systems (DAS) such as adaptive cruise control (ACC) or lane departure warning (LDW) need to perceive the environment using exteroceptive sensors. As DAS become more sophisticated and move from comfort applications such as ACC to safety-critical applications such as automatic emergency braking (AEB), the requirements regarding perception as well as failure modes are becoming more stringent. An automatic emergency braking system can slow down a vehicle with a deceleration of up to  $-1g = -9.8m/s^2$  in case of a perceived collision with another vehicle. This intrusive action is meant to minimize the impact of such a collision. An erroneous deployment of an automatic emergency braking maneuver, e. g. the automatic braking of a car with maximum deceleration going at top speed on an empty highway is considered unacceptable to the driver. In addition to the discomfort and annoyance of the driver, such erroneous deployment can be dangerous and even lethal to

the occupants of the braking as well as the following vehicle in case of a rear-end collision. Hence qualifying conditions must be imposed such that erroneous deployments or false alarms are kept at an absolute minimum - a typical requirement is 1 false alarm per 1 million driven kilometers.

Those qualifying conditions can be applied at every component of the driver assistance system: sensors, perception, controller, and actuation, see [fig. 1](#). In this paper we will focus on the estimation module of the perception component. There, those qualifying conditions can deal with the estimated relative dynamics of a driving situation, i. e. how the perceived objects move with respect to the own (ego) vehicle and whether any of those poses a threat to the ego vehicle. Common criteria are an estimated time-to-collision (TTC), see e. g. [1] or a collision probability see e. g. [2]. On the other hand, estimated objects need not be what they seem to be, e. g. an object could be classified by an identity estimation module as a truck whereas in reality this object corresponds to a passenger car. Even worse, an estimated object might correspond to a real object irrelevant to the vehicle threat assessment, e. g. a soda can, or it can even not correspond to any real object at all - a non-existing object based on spurious radar reflections for example.

Both problems, namely the correct estimation of relative dynamics and an estimation of the confidence or quality of the estimated object can be ameliorated if not completely solved by sensor fusion. This paper is organized as follows: in the first section the types and benefits of sensor fusion will be discussed in general as well as for the special case of DAS. In the next section two improvements due to sensor fusion for an AEB system based upon a radar and a video sensor will be discussed in detail: the improvement in estimation of the relative dynamics (kinematic state estimation) and the improvement of a confidence measure for each track.

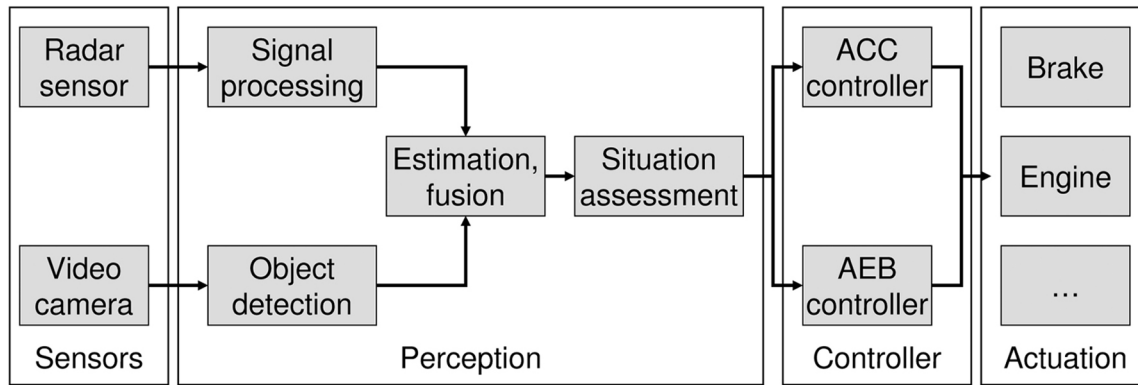


**Figure 1. Simplified block diagram for a radar and video based ACC and AEB system. In the situation assessment module e. g. the ACC track is selected from the set of all tracks as well as the track for which a collision is most likely.**

## SENSOR FUSION

### WHAT IS SENSOR FUSION?

Sensor fusion has its origin in military applications where information from several sources is combined to obtain a better or more complete picture of a battle field or combat situation. Some of the pioneering work including an abstract classification of sensor fusion levels - the JDL model of sensor fusion [3] - was initiated by the US Department of Defense.

A commonly cited definition of information fusion was formulated in an editorial of the journal Information Fusion [4]: “Information fusion encompasses theory, techniques and tools conceived and employed for exploiting the synergy in the information acquired from multiple sources (sensor, databases, information gathered by human, etc.) such that the resulting decision or action is in some sense better (qualitatively or quantitatively, in terms of accuracy, robustness, etc.) than would be possible if any of these sources were used individually without such synergy exploitation.”

Sensor fusion as a subfield of information fusion is the combining of sensory data or data derived from sensory data such that the resulting information is in some sense better than would be possible when these sources were used individually. In particular, sensor fusion deals with the environmental estimation using multiple sensors, see e. g. [5].

### BENEFITS AND TYPES OF SENSOR FUSION

Sensor fusion offers the following general benefits:

- Robustness    redundancy in multiple sensors makes a system more robust in case of partial failure

- Extended coverage    if the ranges of multiple sensors do not overlap or only partially overlap, the joint coverage is extended
- Increased confidence    a measurement of one sensor is confirmed by measurements of other sensors covering the same domain
- Increased accuracy    combining measurements from multiple sensors covering the same domain increases the accuracy of the measured quantities such as distance, speed, etc

Three general types of sensor fusion can be distinguished:

- Complementary    Complementary sensor fusion combines sensory data of sensors whose sensor ranges or fields of view (FOV) do not overlap. An example is the fusion of a forward-looking radar with a backward-looking radar. Generally, fusing complementary data is easy, since the data from independent sensors can be appended to each other.
- Competitive    Competitive sensor fusion combines sensory data of sensors whose sensor ranges are identical or have a large overlap and whose sensor data are of the same type e. g. angle. Competitive sensor fusion can be used for fault tolerance, e. g. an object is confirmed if it is seen by at least two out of three sensors, or for increased confidence in an object, e. g. if an object has been seen by all available sensors.

Cooperative Cooperative sensor fusion combines sensory data of sensors whose sensor ranges have a large overlap in order to obtain new, additional information. Their sensor data need not necessarily be of the same type. This additional information can still be of the same type, e. g. angle, but with an increased accuracy that would not have been achievable with only one sensor; or it can be of a new type, e. g. in inertial navigation the pitch and roll angles can be estimated once speed measurements are available.

More concretely, we have listed salient benefits of sensor fusion for automatic emergency brake (AEB). The sensor configuration under consideration consists of a forward-looking radar and in addition a video sensor. On the right-hand side the corresponding fusion type is indicated.

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|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------|
| <ul style="list-style-type: none"> <li>• Fewer false alarms             <ul style="list-style-type: none"> <li>– Lower confidence for objects detected by <i>only one</i> sensor</li> <li>– More accurate estimation of <i>non-colliding</i> vehicle trajectories                 <ul style="list-style-type: none"> <li>- Object geometry using video width</li> <li>- Better lateral distance</li> </ul> </li> </ul> </li> </ul> | <div>fusion type</div> <div>competitive, cooperative</div> <div>complementary</div> <div>cooperative</div> |
| <ul style="list-style-type: none"> <li>• More true alarms             <ul style="list-style-type: none"> <li>– Higher confidence for objects detected by <i>both</i> sensors</li> <li>– More accurate estimation of <i>colliding</i> vehicle trajectories                 <ul style="list-style-type: none"> <li>- Object geometry using video width</li> <li>- Better lateral distance</li> </ul> </li> </ul> </li> </ul>         | <div>competitive, cooperative</div> <div>complementary</div> <div>cooperative</div>                        |

In the next section we will focus on improvements in lateral distance and in an object's confidence by sensor fusion.

## SENSOR FUSION FOR SAFETY-CRITICAL DAS

### IMPROVING KINEMATIC STATE ESTIMATION BY SENSOR FUSION

#### State estimation

The kinematic estimation module which is situated between the signal processing/object detection and the situation assessment module as in [fig. 1](#) computes an estimated state  $\hat{\xi}$  on the basis of the current and all previous (noisy) sensor measurements  $z$ . This estimate should be close to the real, physical state  $\xi$ . Knowledge of the state is necessary as it is used by the DAS controller component. For a radar-based

driver assistance system such as ACC, the state vector typically contains the relative Cartesian position, velocity, and acceleration, see [fig. 2](#). If a scanning radar is used or video measurements are present, the vehicle's width  $w$  is commonly included:

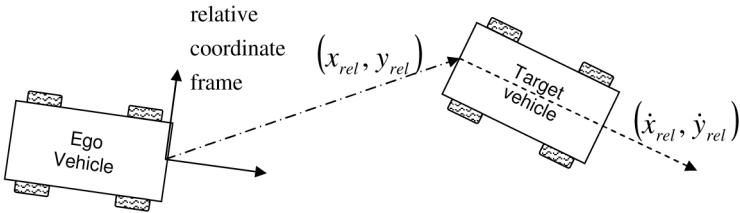


Figure 2. Definition of relative (ego vehicle centered) coordinate system.

$$\xi = (x_{rel}, y_{rel}, \dot{x}_{rel}, \dot{y}_{rel}, \ddot{x}_{rel}, \ddot{y}_{rel}, w)^\top \tag{1}$$

Accelerations are usually included in the state vector because they are required by an ACC controller.

In order to estimate this state, sensory information is necessary. A radar sensor can measure the relative position of a radar target in polar coordinates and in addition the radial velocity exploiting the relativistic Doppler effect, see e. g. [\[6\]](#):

$$z_{radar} = \begin{pmatrix} r_{rel} \\ \phi_{rel} \\ \dot{r}_{rel} \end{pmatrix} \tag{2}$$

A video sensor with object detection capability, on the other hand, typically determines the presence of an object, e. g. vehicle rear views, by applying for example classifiers to rectangular subregions of a video frame, see e. g. [\[7\]](#). As can be seen in [fig. 3](#), a detected object is represented by a tight rectangle around a vehicle rear. The four edges of the rectangle in the 2D pixel image correspond to four

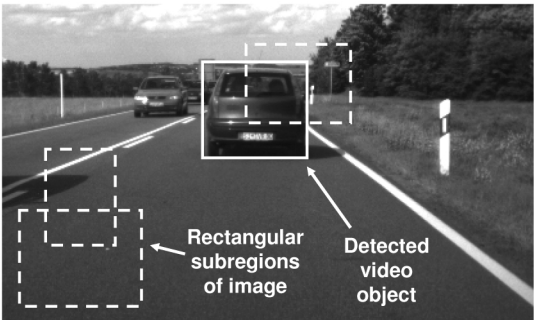


Figure 3. Video object detection using rectangular subregions.