SEFS —
Results on sensor data fusion system development

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Abstract

For driver assistance systems, a thorough perception of the environment becomes more and more important. Often, sensor data fusion systems (comprising typically sensors such as radar and vision systems) are employed, to get an improved picture of the host vehicle's surroundings. The SEFS project is part of the Swedish IVSS programme. The project focuses on methods and architectures for fusion of sensor data. In this paper, some of the main results are highlighted. Findings of the SEFS project include a data fusion structure and architecture, tracking methods as well as vehicle and road models plus related parameter estimation.

Keywords: Sensor Data Fusion Systems, Object Tracking, Radar Sensor Models, Automotive Safety, Advanced Driver Assistance Systems

1 Overview of the fusion system developed in the SEFS Project

The objective of the work in the SEFS project is to determine a consistent representation of the environment of the ego vehicle based on different sensor observations. The perception of the environment includes detecting, tracking and classifying surrounding objects as well as recognizing lanes and observing the host vehicle's position on the road. From the sensors, observations are received mainly on a detection level.

In order for the fusion algorithm to determine how to combine information originating from several different sensors, also including previous knowledge, it relies on two types of statistical models. One to describe the information in observations coming from the sensors, i.e. measurement or sensor model, and the other to model how the quantities of interest behave as a function of time, i.e. process or motion model. How well both these models describe the true nature of the measurements and the motion of e.g. vehicles, will greatly affect the accuracy of the fused result.

Some major findings of the SEFS project will be summarized in this contribution. Section 2 gives an overview of the system architecture. An enhanced radar sensor model is described in section 3. A further important system component are motion models, discussed in section 4. In addition to tracking moving objects, the estimation of road parameters is a relevant task, explained in section 5.

2 Sensor data fusion design architecture

Several practical issues need to be considered when designing a real-time sensor data fusion system using online sensor data. Apart from solving a recursive estimation problem, the system must meet automotive system requirements regarding cost, computational load, robustness and estimates produced. It is also desirable to have an architecture that allows code to be re-used through different development steps, i.e. it should be straightforward to go from the

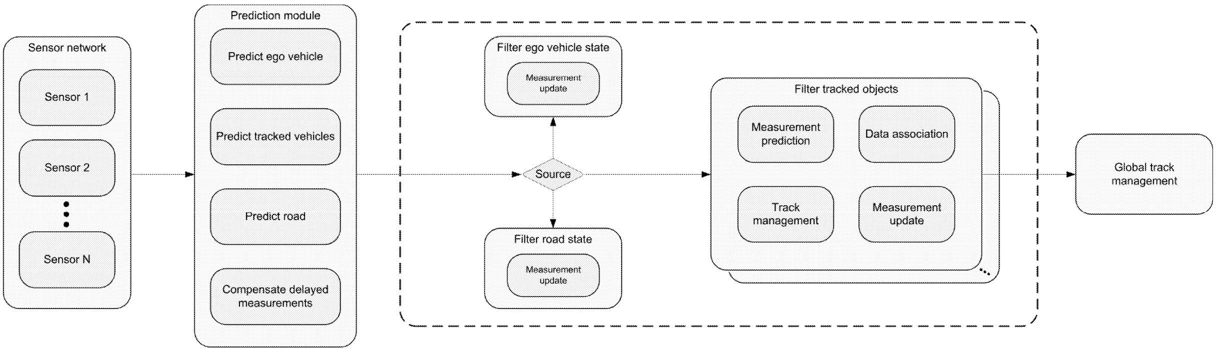


Figure 1: Fusion algorithm functional architecture. The large block is called once for each received measurement, executing necessary prediction and filter modules in the correct order.

research system to an in-vehicle system in order to make use of recent innovations. Designing a fusion system considering all these aspects is truly a challenge.

In [1] we present a sensor data fusion functional architecture tailored for development of automotive active safety systems. It originates from experiences made while designing and implementing the SEFS data fusion system. The fusion strategies are thoroughly presented in [2], whereas the hardware environment is described in [3]. Our proposed functional architecture is designed such that the fusion system is easy to maintain, upgrade and re-use, making it relatively easy to exchange sensors and develop software components. The proposed modularity is clearly seen in Figure 1, showing the proposed functional architecture. The design also allows for formal treatment of practical issues such as fusing delayed data, or data from asynchronous sources.

The fusion system used and described in [1, 2] is based on the Unscented Kalman Filter [4] and exemplifies that the proposed strategies can be implemented using rapid prototyping tools from which we can automatically generate c-code. In order to derive to what extent the proposed architecture limits the performance of a tracking system, a limited set of sensors have been used to compare the tracking results with that of a sensor specific tracker available on the market. Results indicate that the performance of a tracking system implemented using the proposed architecture is comparable with that of a dedicated sensor tracker, while enjoying the flexibility that follows from using the proposed design approach [1].

3 Tracking vehicles using radar detections

Traditional tracking systems used in, *e.g.* airborne radar applications, are typically built around a point source assumption. For these applications it is common that the extent of a target is small in relation to the resolution of the radar sensor, and therefore the object is seen by the radar as a point. However, in automotive applications where the distance between the sensor and the measured object is much smaller, this is seldom the case. For these situations, vehicles generate multiple radar detections, and hence the point source assumption is violated. Obviously, if we are able to model from where on the vehicles the multiple radar measurements originate there is a possibility to extract more detailed information about the objects.

In [5] a model is proposed to simulate radar returns from vehicles. The proposed model stipulates that radar mainly receives reflections from a discrete set of points, so called *reflection centers*, on the vehicle. These reflection centers are regarded as locations on the vehicle where it is more probable to get a strong radar return, and how they are positioned on a vehicle is shown in Figure 2. Additionally, the model takes the limited resolution of a radar sensor into account, and treats measuremens from closely located reflection centers accordingly if they are unresolvable.

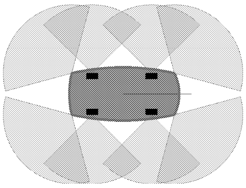


Figure 2: A schematic birds eye view of the configuration of reflectors suggested in [5], where plane reflectors are positioned at the vehicle sides and point reflectors are placed in the wheel housings and corners of the vehicle. Associated with each point reflector is a visibility region, depicted by cones, indicating that the reflector is only visible if the sensor is positioned within this field of view.

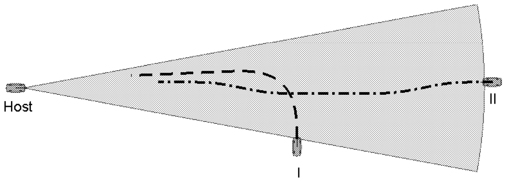


Figure 3: Two simulated scenarios used for evaluation of the proposed filter framework. In scenario I, the target vehicle starts at a speed of 18 km/h and temporarily decelerates while turning. In scenario II the target vehicle performs two lane change manoeuvres while driving at a constant speed of 32 km/h. The host vehicle remains stationary in both scenarios.

Although, this simulation model has many promising properties, it was originally developed for simulation purposes and, hence, lacks the probabilistic description required if it should be used in a tracking framework. In [6], we propose modifications and generalizations to alter the model into a family of sensor models more suitable for tracking. Furthermore, in a tracking framework we need to handle uncertainty regarding the origin of the detections, *i.e.* the data association problem. To reduce the complexity of this problem in tracking extended objects, [6] proposes to associate radar detections with groups of vehicle reflectors instead of associating detections with single vehicle reflectors or reflector clusters. Each group contains a set of reflectors, where each reflector is likely to be clustered with at least one other reflector in the group. Based on this sensor model a tracking algorithm is desiged that is able to utilize the information of multiple detections from a vehicle.

The tracking performance of the proposed framework is evaluated using simulated radar data obtained in regards to the two trajectories displayed in Figure 3, both of which can be considered challenging for a radar tracking algorithm. Radar measurements are simulated for both scenarios at a rate of 40 ms, using the simulation model in [5]. Important to note is that target detections are generated without the approximations suggested in the filtering framework and, hence, the simulation model is more detailed than the model in the evaluated filter.

The simulated data from both scenarios is filtered using the proposed filter framework and

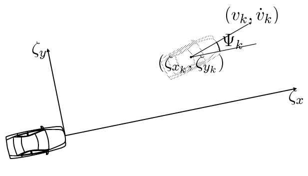
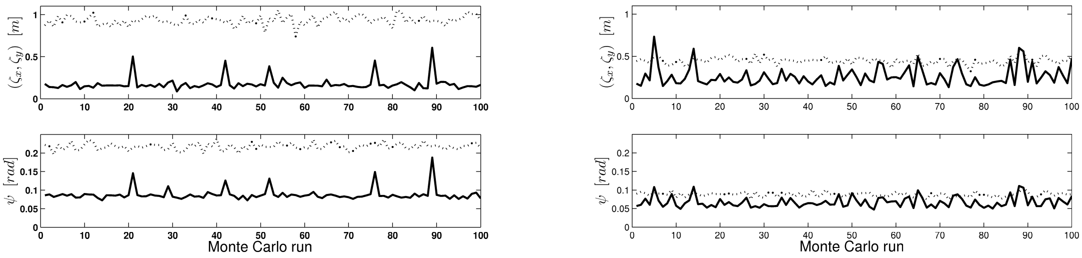


Figure 4: The state vector for both filters consists of target vehicle position, $(\zeta_{x_k}, \zeta_{y_k})$, heading, Ψ_k, velocity, v_k and acceleration, $\dot{v}_k$, expressed in a local host vehicle coordinate system.



(a) Scenario I

(b) Scenario II

Figure 5: Root mean square error (RMSE) for position $(\zeta_{x_k}, \zeta_{y_k})$ and heading, Ψ_k, for the proposed filter framework (solid line) and reference filter (PDAF) (dotted line).

a reference probabilistic data association filter (PDAF) [7]. Both filters use the same state vector description shown in Figure 4 with equal dynamic noise covariances ($\sigma^2_{\ddot{\Psi}} = 1/16$, $\sigma^2_{\ddot{v}} = 9$). In the PDAF, at most one measurement can originate from the object and consequently, additional measurements are regarded as clutter. The reference filter compensates for offset errors using the geometry of the vehicle and its estimated position.

Figures 5(a) and 5(b) show the root mean square error (RMSE) of estimated position and heading for 100 Monte Carlo simulations of scenario I and scenario II, respectively. In the first scenario a significant improvement in performance for the proposed filter in comparison to the reference filter is observed, whereas in the second scenario this difference is much smaller. The variation in performance is likely explained by the fact that scenario I is more advantageous for an extended object representation capable of using all detections, in comparison with the PDAF, which will be less certain when the measurements start to spread. One should however, also consider that the increase in performance comes at a price of increased sensitivity to noise. Although, the proposed filter outperforms the PDAF for most of the Monte Carlo runs, some noise realizations do cause spikes in the RMSE for the proposed filter. Despite this increase in sensitivity, the performance is still kept within acceptable levels even in the worst case scenarios.

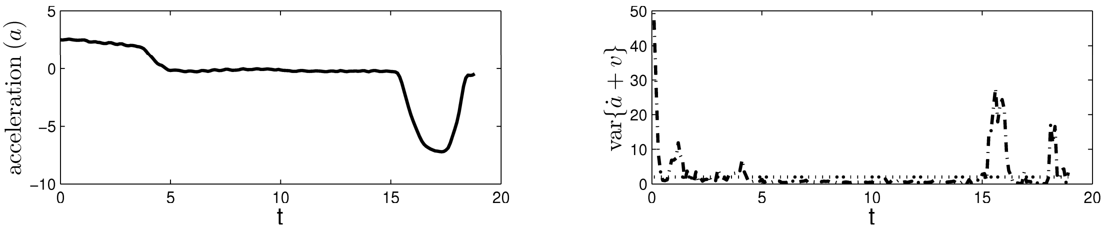
4 Vehicle motion model for improved predictions and situation assessment

Reliable and accurate vehicle motion models are, for a number of reasons, of vital importance for automotive active safety systems. First of all, these models are necessary in tracking algorithms which provide the safety system with information. Second, the motion model is often used by the safety application to make long term predictions of the future traffic situation in order to determine if, when and how to intervene.

Our research, presented in [8, 9, 10, 11, 12], is motivated by the fact that the motion of a vehicle under normal conditions is controlled by the driver, a non-controversial statement that most of us can agree to. Even so, many vehicle motion models ignore this fact or alternatively model the driver influence as a zero-mean white Gaussian noise process. We have developed an alternative motion model framework, where the expected action of the driver is included as a control input. This enables us to consider and model different driver intentions, such as the desire to drive safe and comfortably, and how they influence the motion of the vehicle.

The proposed modelling framework is based on a set of postulates, governing driver actions.

1. *The driver controls the motion of the vehicle by steering and adjusting the acceleration.*
2. *In normal traffic, the actions of a driver can be divided into a set of different categories, e.g. making a lane change or performing an overtake.*



(a) Acceleration profile

(b) Calculated variance

Figure 6: A vehicle is performing a braking manoeuvre, described by the acceleration profile, and the variance of the predicted vehicle control signal, including the process noise v, is calculated using our model. The variance of a Constant Acceleration model is included as reference.

3. *The driver strives to control the car in a safe and comfortable manner, and at a preferred velocity.*
4. *The driver plans ahead and tries to find the optimal route, such that the driver preferences are considered for the near - and not only the immediate - future.*

These postulates are used to set up a cost function, $\mathrm{cost}(\mathbf{x}, \mathbf{u_{1:N}})$, taking as input the initial state of the vehicle, $\mathbf{x}$, and a sequence of control input signals $\mathbf{u_{1:N}} = [\mathbf{u_1} \ldots \mathbf{u_N}]$. The vehicle state vector includes parameters such as the road and the position and dynamics of surrounding vehicles. The expected control input is obtained by minimizing the cost function, i.e. the driver is regarded to be an optimal controller of the vehicle. Differences in driver behaviour, explaining why drivers do not behave identically in similar situations, are modeled by a set of driver preferences also included in the state vector. These preferences are treated as a stochastic parameter which, given past observations of driver control input, can be marginalized in order to calculate a posterior driver control input distribution. Hence, uncertainties regarding expected driver control signals are large in situations where we expect minor changes in driving preferences to have a large impact on the longitudinal control parameter. The dynamic behaviour of the posterior distribution is illustrated in Figure 6, showing the acceleration of a vehicle during a braking manoeuver together with the variance of the expected driver control signal, for the proposed model and a commonly used reference model. The variance of the reference models assumes the variance to be constant, whereas the variance calculated by the proposed model is large when some drivers are likely to brake earlier than others. This is a useful feature that drastically improves the accuracy of the predicted distribution. In contrast to our model, the reference model will be overconfident in dynamic situations and unnecessarily careful in static scenarios. By tailoring the presented framework to specific applications, predictions are made more accurate and applications can benefit from a deeper understanding of the current traffic situation. The framework has been evaluated with respect to its ability to predict driver actions in a braking scenario, using Differential GPS measurements as reference, and predicting and detecting lane changes.

This framework was originally presented in [8], and was further developed in [9] where the original framework is extended by introducing multiple manoeuvre hypotheses. In [13][1], the framework is enhanced by considering the interaction with other vehicles and, more importantly, with the ability to estimate the uncertainty regarding the predicted driver control input. The latter is a very useful property when applying the framework in e.g. tracking algorithms.

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[1] This paper is currently in a review process. Preliminary results are available in [10, 11, 12].

5 Road Geometry Estimation

In [14] we present a new formulation for the rather well studied problem of integrated road geometry estimation and vehicle tracking. This framework improves the vision estimate of the road geometry by fusing it with radar measurements of the leading vehicles and information from proprioceptive sensors (e.g. velocity or yaw-rate sensors). The idea that the motion of the leading vehicles reveals information about the road geometry was mentioned the first time in [15]. Hence, if the leading vehicles can be accurately tracked, their motion can be used to improve the road geometry estimates. Furthermore, we use a single track dynamic model of the ego vehicle allowing us to further refine the estimates by incorporating several proprioceptive sensor measurements from the CAN bus. The so called cornering stiffness parameters of the single track model describe the tire-road contact and are unknown and even time-varying. Hence, in order to fully make use of the single track model, these parameters have to be identified. In [16] we provide a method for recursive identification of the cornering stiffness parameters to be used on-line while driving.

A good polynomial approximation of the shape of the road is given by

$$y = l + \delta_r x + \frac{c_0}{2}x^2 + \frac{c_1}{6}x^3, \tag{1}$$

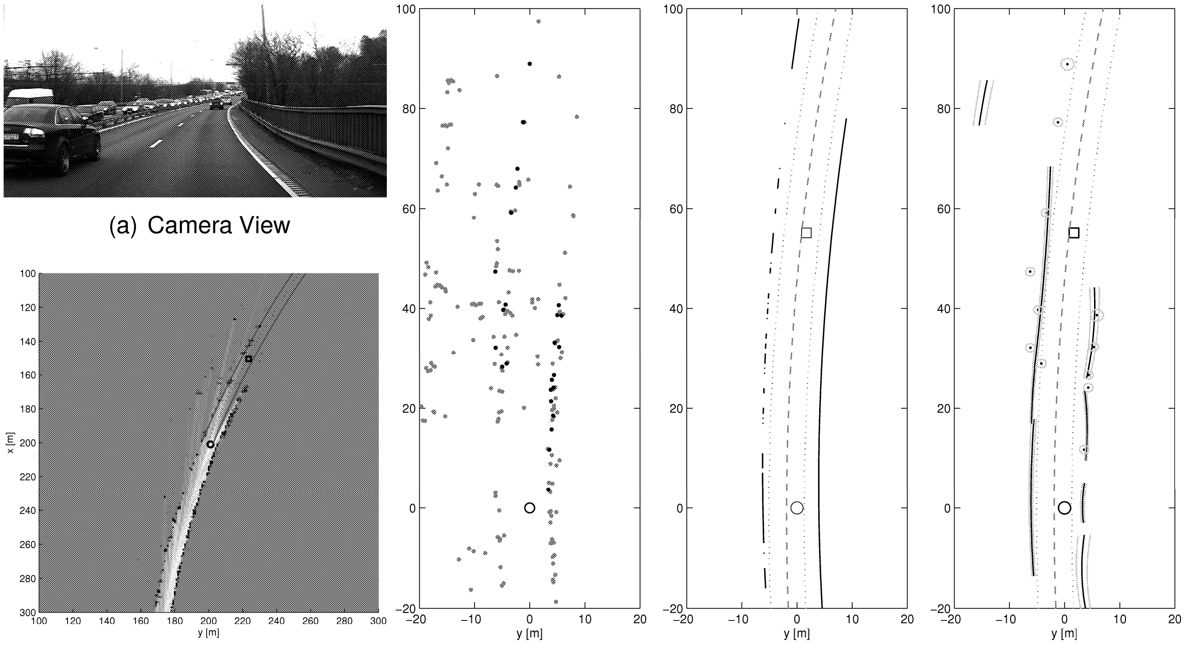
in an ego vehicle fixed coordinate frame (with x in longitudinal direction and y in lateral direction), see e.g., [17, 18]. The angle between the longitudinal axis of the vehicle and the road lane is δ_r. The curvature parameter is denoted by c_0 and the offset between the host vehicle and the white lane marking is denoted by l.

Moreover, we use information already present in the radar detections concerning stationary targets along the road, to provide a reliable estimate of the free space in front of a moving vehicle. We compare three conceptually different methods to estimate stationary objects or road borders, and illustrate them with the traffic situation shown in Figure 7(a) with associated radar measurements in Figure 7(c).

The first method considered is occupancy grid mapping (OGM), which discretizes the map surrounding the ego vehicle and the probability of occupancy is estimated for each grid cell. More details about the OGM are given in [19] and a solid treatment can be found in [20]. The resulting bird's eye view is shown in Figure 7(b). The second method, thoroughly described in [21], applies a constrained quadratic program (QP) in order to estimate the road borders. The problem is stated as a constrained curve fitting problem. The result using a linear model containing four parameters is shown in Figure 7(d). The third method, described in [22], associates the radar measurements to extended stationary objects and tracks them as extended targets. We represent the stationary objects as points, with sources such as delineators or lampposts, or lines, where measurements stem from e.g. guard rails or concrete walls. For the given example the estimated points and lines are shown in Figure 7(e). Finally, the estimated road shape according to (1) is illustrated by the dashed gray lines in Figure 7(b), (d) and (e).

6 Conclusion

This contribution gives an overview of the main findings of the SEFS project. It first describes the fusion structure identified by the project and then elaborates the fusion architecture. Then, algorithmic findings are highlighted in summary, giving references for more detail. Results include the tracking of moving vehicles as well as motion and road models and the related task of parameter estimation. For the tracking of vehicles, the modelling as extended targets, consisting of a set of different reflection points has been investigated and found to be relevant. Improved motion models open the opportunity for improved tracking and situation assessment systems. For the road geometry, methods have been shown for how to utilize external and



(a) Camera View

(b) OGM

(c) Measurements

(d) Constrained QP

(e) Extended Targets

Figure 7: The camera view of a traffic situation is shown in Figure (a). Figure (c) shows the bird's eye view of the radar measurements, and Figure (b), (d) and (e), the estimated stationary objects along the road. The circle is the ego vehicle, the square is the tracked vehicle in front and the dashed gray lines illustrates the estimated road curvature.

internal sensors to improve the road parameter estimation. All described methods together contribute to the SEFS system for sensor data fusion.

Project Partners

The SEFS project is a cooperation of Volvo Technology AB, Volvo Cars Cooperation, Volvo 3P, Mecel AB, Chalmers University of Technology and Linköping University.

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