Data Fusion considering 'Negative' Information for Cooperative Vehicles

Karin Tischler and Heike S. Vogt

Institut für Mess- und Regelungstechnik, Universität Karlsruhe (TH)
D-76128 Karlsruhe, tischler at mrt.uka.de

Abstract: Negative information provides important additional knowledge that is not exploited for sensor data fusion tasks by default. This paper presents a new approach to incorporate such information about unoccupied, observed areas or missing measurements in the Kalman filtering process. For this purpose, a combination with a grid-based method is proposed to generate a visibility map. This enables a plausibility check and an enhanced understanding for the collaborative perception of the environment with multiple cognitive vehicles. Results from a realistic traffic simulation are presented.

1 Introduction

The field of information fusion has a large amount of applications in advanced driver assistance systems. Most systems require extensive knowledge and understanding of the complex vehicle's environment. The collaborative perception by an inter-vehicle network promises a multitude of improvements. Each vehicle acts as sensor and fuses its information with the perception of others to an enhanced description of the environment. Up to now, we only consider positive measurements in this data fusion. The knowledge about unoccupied observed areas is not modelled explicitly, even though such regions are important for the trajectory planning of a moving vehicle. Considering the special application of cooperative vehicles, negative information is required for a meaningful plausibility check. The recognition of contradictions in overlapping measurement areas leads to different interpretations regarding the reliability of the sensors or the existence of a detected object.

By negative information the general case is described that within a sensor controlled area no objects are detected. With his illustrative Eiffel Tower example Thrun [3] already shows that negative information is more difficult to deal with in an adequate way than positive information. Depending on the situation, the lacking of a measurement can be expected, explainable or leads to a contradiction. For the missing, three reasons are distinguished [2]. The expected object can be out of range, it is occluded or the measurement is incorrect due to a sensor failure. For a meaningful interpretation of the negative information, the measurement process and the field of view have to be modelled as exactly as possible. Additionally, occlusions by other dynamic or stationary objects have to be considered.

2 Concept and Implementation

The integration of negative information is already interesting for the tracking of single sensor detections but it becomes necessary for the interpretation and the plausibility check of data from multiple distributed sensors. The system for a collaborative perception of the environment with multiple vehicles is described in [4]. To fuse the perceptions of distributed sensors, we assume that all agents are equipped with an inter-vehicle communication, a system for the spatiotemporal alignment and environmental sensors. The standard tracking techniques are not able to deal with two-dimensional negative information for they use positive measurement data only. To handle the spatial information of multiple moving fields of view, the utilization of a grid-based method is an expedient approach.

In our concept shown in Fig. 1 we represent the negative information by an additional grid that covers the whole interesting region with rectangular cells of constant size. In the grid map, the field of view of each single sensor S_1 to S_n is registered according to the vehicle's pose. This leads to the so-called visibility map. Additionally, we model the detection probability P_{D} over the field of view of every sensor. Thereby, a specific probability is assigned to each cell depending on the variable sensor configuration. An object is detected by the sensor with the corresponding detection probability of its cell. Furthermore, the occlusion of other grid cells can be noticed. In the visibility map, observed unoccupied areas are documented and in case of overlapping fields of view inconsistencies become obvious in the plausibility check. The visibility map is updated for each measurement interval.

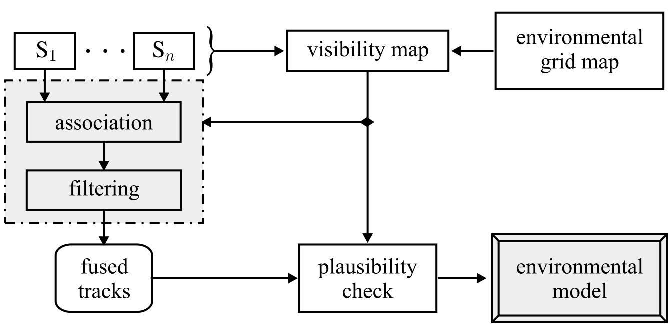


Figure 1: Concept of integrating negative information in the fusion process.

As all grid-based methods, the visibility map itself is not expedient for the data association, filtering and tracking of fast moving vehicles. Therefore, we combine the grid with the centralized tracking algorithm. First, the object measurements from multiple vehicles are transformed into global Cartesian coordinates. The multiple object tracking using Kalman filters with a constant velocity model yields directly fused tracks. For the association of new measurements from the sensors S_1 to S_n we adopt the cheap Joint Probabilistic Data Association (cJPDA) filter [1]. The association is improved by *a priori* information of the visibility map. At the end of a measurement interval, the updated tracks are compared with the expectations from the visibility map to check the plausibility. For the combination of the visibility map with the tracking procedure, we introduce a check matrix $\mathbf{CP}_{ij}$ for each pair of sensor and object $(i,\, j)$:

$$\mathbf{CP}_{ij} = \begin{pmatrix} \text{time step} \\ \text{detection probability} \\ \text{update mark} \\ \text{failure mark} \end{pmatrix} = \begin{pmatrix} \dots & t_{i-1} & t_i \\ \dots & P_{\mathrm{D}}(t_{i-1}) & P_{\mathrm{D}}(t_i) \\ \dots & \dots & UM(t_{i-1}, t_i) \\ \dots & \dots & FM(t_{i-1}, t_i) \end{pmatrix} \tag{1}$$

$\mathbf{CP}_{ij}$ contains all time steps during the sensor and object life cycle defining the measurement intervals $\mathcal{J} = (t_{i-1},\, t_i]$ and the corresponding detection probability $P_{\mathrm{D}}(t_i)$. The update mark UM is set to 1 and the failure mark FM to 0, if the track of the object i is updated by a measurement of sensor j as expected. Missing detections ($UM = 0$) leading to a contradiction between the expected and the actual measurement are recognized by comparing the update mark with the detection probability. After an occlusion check, the sensor failure is marked by setting the failure mark FM to 1. At the end of each interval, tracks are predicted or terminated according to their covariance, the visibility map is updated and the markers reset.

There are different possibilities to interpret and handle information about a missing detection due to sensor failure. If we suppose an irregular sensor failure, the function of the sensor could be defective. This could be considered by reducing the reliability of the sensor detections according to the failure mark, e. g. by an adjustment of the association weight in the cJPDA filter. Another method is the reduction of the sensor's detection probability in the visibility map. On the other hand, a missing but expected measurement can be interpreted to the disadvantage of the object. Increasing the covariance of the process noise could be an adequate means for this. Exemplarily, we use negative information to adopt the existence probability P_{exist} of a detected object. By the first detection, the existence probability is assumed to be 50%. We suppose to have N sensors in whose field of view the object is located, m sensor vehicles thereof which have detected the object and n sensor vehicles which have failed contrary to expectations the detection. At the end of each measurement interval $\mathcal{J}$, the existence probability of the object is adjusted according to the following linear model:

$$m > n: \; P_{\text{exist}}(t_i) = P_{\text{exist}}(t_{i-1}) + \epsilon\,; \tag{2}$$

$$m \leq n: \; P_{\text{exist}}(t_i) = P_{\text{exist}}(t_{i-1}) - \epsilon\,. \tag{3}$$

m and n can be determined by means of the update and failure marks. The value ϵ of changing is arbitrarily chosen. The existence probability is increased if the majority of the expected sensors detects the object. The upper limit of the probability is determined according to the sensors' reliability and the number N of sensors. The confidence in the existence of an object will be higher if more than one sensor validates the detection.
If the majority of sensors fails unexpectedly, P_{exist} is decreased in order to take into account the contradiction between the sensor measurements. In our model, the decreasing of

the existence probability is described as limited by a minimum value:

$$n > 0 : \quad P_{\text{exist, min}} = \frac{m}{m+n} = \frac{m}{N} \, . \tag{4}$$

In case of at least one unexpectedly missing measurement, $P_{\text{exist, min}}$ is chosen as the ratio between the number of sensors m which have detected the object and the amount N that should have seen the object. The existence probability is valuable as new criterion for the termination of an object track.

3 Results

To evaluate our approach, we generated a traffic scenario as depicted in Fig. 2 with our microscopic traffic simulation that provides realistic measurement data, e. g. of a radar sensor. The cognitive vehicle S_1 is driving straight forward on the left lane of a road, detecting another vehicle #1 in front of it. While #1 is crossing the junction (time t_1 – t_2), it is detected by S_1 and S_2. From the southern side street, S_2 turns parallel to S_1 on the right lane. Now, their fields of view are overlapping and vehicle #1 is detected by both (t_3 – t_{end}). Via communication the cooperative vehicles know each other. When the fields of

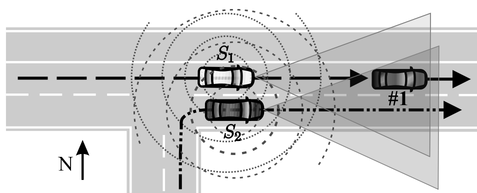
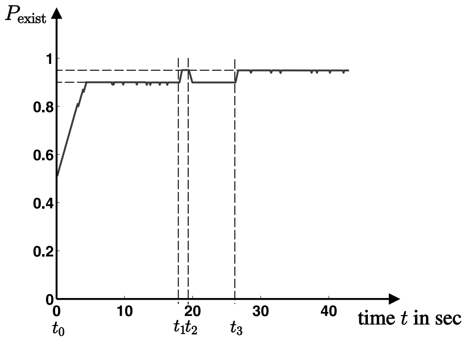
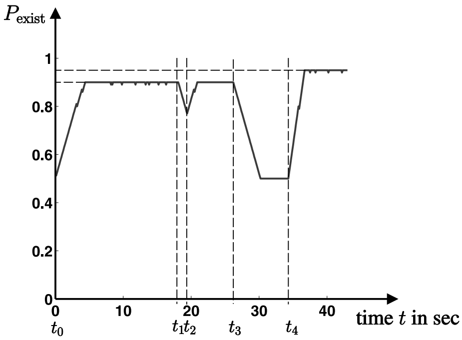


Figure 2: Simulated scenario.

view of S_1 and S_2 are overlapping in the junction, S_1's detection of object #1 is validated by the measurement of S_2. Therefore, the existence probability of #1 in Fig. 3(a) increases compared to the probability feasible by a single sensor.
To test the algorithm in case of sensor failure we incorporate such failures in the simulation. The detection of #1 by S_2 is missing during the junction crossing and from t_3 to t_4. The fused detections yield a continuous track of #1, but the existence probability in Fig. 3(b) decreases due to the unexpected contradiction between the measurements which is not explainable by occlusion. Without the negative information in the visibility map, the missing detections of S_2 would not be considered in the fusion process.



(a)



(b)

Figure 3: Existence probability for single and double detection of object #1 in the simulated scenario (a) and in case of unexpected sensor failure (b).

4 Conclusions

The concept of incorporating negative information in the sensor data fusion process of cooperative vehicles yields interesting new possibilities for the understanding of the situation. It enables a plausibility check in overlapping measurement areas with consideration of observed vacant areas. The consistency of the collaborative description of the environment is increased. Future work will analyze different effects of utilizing negative information to integrate contradictory information due to different types of faulty detections.

Acknowledgement

The author gratefully acknowledge the contribution of the Transregional Collaborative Research Centre on Cognitive Automobiles (SFB/Tr 28) granted by the German Research Foundation (Deutsche Forschungsgemeinschaft, DFG).

References

[1] Y. Bar-Shalom, *Multitarget-Multisensor-Tracking: Applications and Advances*, Boston Artech House, 2000.

[2] J. Hoffmann, M. Spranger, D. Göhring, M. Jüngel, *Making Use Of What You Don't See: Negative Information in Markov Localization*, Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems, 2005.

[3] S. Thrun, W. Burgard, D. Fox, *Probabilistic Robotics*, MIT Press, 2005.

[4] K. Tischler, B. Hummel, *Enhanced Environmental Perception by Inter-Vehicle Data Exchange*, Proc. IEEE Intelligent Vehicles Symposium, Las Vegas, USA, 2005.