

HANDLING CONTRADICTORY SENSOR DATA IN ENVIRONMENT MAPS FOR ADVANCED DRIVER ASSISTANCE SYSTEMS

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Abstract: Advanced driver assistance systems require environment information like position of other vehicles or lane markings. Since different systems on a single vehicle need similar data, a known approach is to create a common environment model. Using dynamic state estimators during sensor data fusion, noise from measurements can be minimized and the state and its variance can be approximated.

However, the precision of state estimation seems not to be the bottleneck of the whole system. Sensors for environment perception sometimes produce false positives or false negatives, so that sensor data fusion must be able to handle contradicting data. This paper introduces a new method to estimate the state of a driving tube and applies it to sensor measurements.

1 Introduction

A multitude of driver assistance and driver information systems can be found in present vehicles to increase driving comfort and safety. Navigation systems provide information about a possible route and its current threats like accidents or traffic jams. Lane departure warning and lane change assistance systems inform the driver in the case of potentially dangerous situations. Anti-lock Braking System (ABS) and Electronic Stability Control (ESC) can reduce control loss in vehicle dynamics borderline situations.

Driver assistance systems can be subdivided into two categories: The first contains systems which require data only about the own vehicle state. These can be reliably measured at suitable vehicle sites. Besides ABS and ESC, to this category also belong traction control and adaptive lighting systems which need measurements of wheel velocities, steering angle and yaw rate.

The second category consists of advanced driver assistance systems like adaptive cruise control (ACC), lane change assistance and automatic emergency braking systems which need additional information about other traffic participants. The detection of lane markings is a basic requirement of some driver assistance systems like lane departure warning system as well. These environment data must be gained by additional sensors like lidar, radar, sonar or camera sensors.

All these sensors have in common that they do not measure relevant quantities exclusively but a multitude of data which must be pre-processed and filtered to get the required information.

For example a camera sensor records digital pictures which consists of many pixels with different brightness and colour. Image processing algorithms have to be applied to extract the required quantities. During processing of radar signals, multiple reflections must be suppressed. Lidar and radar sensors produce a lot of reflection points which must be associated to the correct objects.

All sensors mentioned above may not detect a relevant target or they may pretend to detect a non existing target. This can influence the quality of the environment perception and therefore might reduce the performance of driver assistance systems.

2 Uncertainty determination and reduction

In the environment model, different types of uncertainty occur: Since every measurement is more or less noisy, there is always a difference between the real and measured state of an object. Several measurements can be used in dynamic state estimators to minimize noise and quantify the uncertainty of an objects state. The uncertainty of the state can be expressed with its covariance matrix.

The most common dynamic state estimator is the Kalman filter which has been published and applied in several variants successfully [BSLK01]. An important part is the so called predictor-corrector method: The current estimation is predicted to the measurement time using a dynamic model and corrected through that measurement. A dynamic weight factor is used which determines if the current measurement is used more or less to correct the estimation. Filtering using dynamic state estimators is state of the art, so this paper will not deal with it.

Beside the uncertainty of an objects state, the existence of the object itself is an uncertain factor which has to be examined. Driver assistance systems have to make discrete decisions often based on the belief in target objects. They also have to regard the possibility of making false decisions when balancing between different possibilities. Sensor data fusion should support the application by quantifying the existence probability for each object and also the trafficability of a certain area in the environment model.

3 Sources for existence estimation

To estimate an existence probability for objects, several information sources can be combined:

1. Measurement: The most obvious existence indicators are non-contradicting measurements of an object

2. Appearance plausibility: A target object should appear at the border of a sensors field of view
3. Model likeness: Every tracked target object should move according to its dynamic model
4. Lifetime plausibility: A target object should only disappear if it leaves a sensors field of view

This paper will focus on measurements as an existence indicator and on their plausibility. Plausibility is determined by checking measurements of an object against measurements of free areas. Objects should not appear and disappear in areas which have been measured as free. Hereby, it must be considered that this field of view is not only limited by its range but also through other objects which may obscure large areas.

Hence, an important source of plausibility is a map which contains information about the field of view and the free area. For this purpose, an occupancy grid has to be build for generating such a map dynamically. The grid is later used to check the trafficability of the cars planned trajectory.

4 Inter-Cell Dependency Problem

Occupancy grids are used to build an environment map containing information about occupied and free areas. They discretize the space into square cells where each of them contains a state. Occupancy grids have already been widely used for sensor data fusion using different sensors like laser range finders [YAL06] or sonar sensors [ME85]. They also have been applied to automotive applications [CPL⁺06].

A common model to express a measurement with an uncertain position is the Gaussian distribution. It is projected on the occupancy grid and all affected cells are updated with the overlapping area of this probability density function. For performance reasons, only those cells are updated which overlap the distribution significantly. Often used update algorithms are Bayes or Dempster-Shafer theory which calculated a new state for a single cell [ME88].

These algorithms can provide a statistical accurate estimation of the occupancy probability of each single cell in the occupancy grid. However, many application need a single accumulated probability of a set of cells and not many probabilities of single cells. For this purpose, a query algorithm for a set of cells has to be developed.

When using the classical fusion algorithms like Bayes or Dempster-Shafer, query algorithms cannot provide a statistically correct value about a set of cell. In general, it is undecidable whether a given probability represents the state of a set of cells statistically correct assuming that each cell contains only probabilities about its own state.

The proof is shown in figure 1. Two equivalent sets of cells are constructed there. They may represent a one-dimension driving tube and the application wants to have a statistical

accurate statement about the trafficability. The left figure shows a measurement which lies completely inside this driving tube causing a trafficability probability of zero¹. The right figure represents two measurements which expectancy values are located on the driving tubes border. Since there is a 0.5 chance for each measurement that it is outside of the driving tube, there is a 0.25 chance that this driving tube is free assuming statistical independent measurements. Since both set of cells are equivalent, there is no function which can separate these two cases.

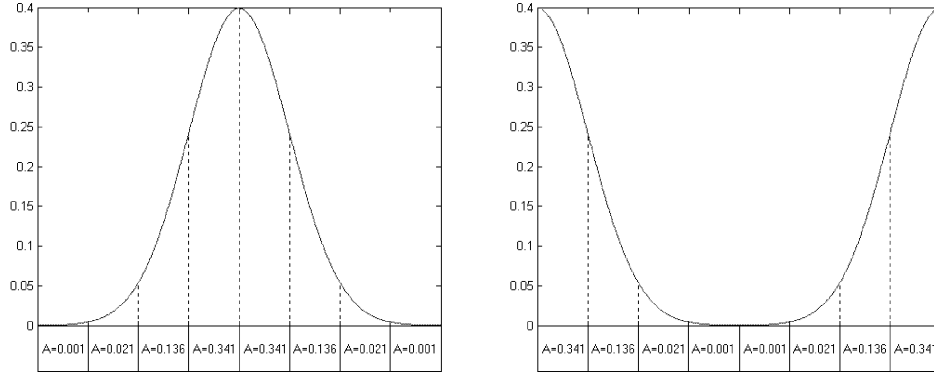


Figure 1: A single measurement completely inside the driving tube and two measurements which are exactly on the border of the driving tube.

Depending on the number of measurements and their constellation, large differences between estimated and real occupancy probability can arise. To quantify this, another occupancy grid is constructed artificially.

It is assumed that n Gaussian distributed measurements are fused into the occupancy grid in such a way that each of them is lying partially and nonoverlapping in the queried set of cells. Each measurement overlaps the relevant set of cells with an area of $\frac{1}{n}$. Under the constraint that every measurement is independent to all other measurements, the probability F that all cells of this set are free is:

$$F(n) = \left(1 - \frac{1}{n}\right)^n \quad (1)$$

If the number of measurements is increased, the free probability converges to a constant:

$$\lim_{n \rightarrow \infty} F(n) = \frac{1}{e} \quad (2)$$

¹Every Gaussian distribution covers an unlimited amount of space. For simplification, we do not consider cells which are far away from the measurements expectancy value. To avoid loss of generality for this proof, the driving tube has to be extended in such a way that it covers an unlimited number of cells and that the distance between all measurement is unlimited, too.

As a result, we have a free probability up to 0.36 depending on the number of measurements compared to 0.0 when summing up all probabilities.

The reason of the estimation differences is the loss of information during fusion process: The degree of dependence of one cell to others is not represented in the occupancy probability of a single cell causing the "Inter-Cell Dependency Problem". A careful development of fusion algorithm consistent to query algorithm has to be done to solve this problem.

5 Occupancy Grid Building

In this section, fusion algorithms for sensor data are presented. Sensor data may describe an occupied area according to a point or line model. Additionally, a free area model is provided, too. Together with the query algorithms in section 6, they form one solution for the Inter-Cell Dependency Problem.

To fuse information of free areas, sensors providing depth information like a stereo camera or a laser scanner are needed. Assuming that the area between reflection point and sensor is free, these sensors can provide large areas which have been measured as free. If there is no reflection point, the evidence for a free area decreases with increasing range.

In the following model, a core area from 0 until R_{Min} is defined, where a maximum evidence value for a free area is reached. With increasing range, the free area evidence is falling linearly until the distant is equal to R_{Max} . At this point, the maximum sensor range is reached, so that there is no further information about states of more distant cells.

The probability that the area of the cell C with coordinates x, y is free assuming a reliability factor τ of the measurement is:

$$C_F(x, y) = \max \left(0, \frac{R_{Max} - \max(\sqrt{x^2 + y^2}, R_{Min})}{R_{Max} - R_{Min}} \right) \cdot \tau \quad (3)$$

Beside information about free areas, also static objects can be fused into the occupancy grid. For static objects like guard rails or standing vehicles, two different models are used for occupancy probability calculation: Depending on a sensor output after pre-processing, a point model or line model is applicable.

In the following we assume objects which have beside position information p_x and p_y also estimated variances σ_x and σ_y . Variance estimation can be done beforehand for any sensor or they can be estimated dynamically using tracking algorithms like a Kalman filter. Beside variances, a reliability factor τ has to be defined for every measurement. This value becomes important if there are contradicting measurements and sensor data fusion has to decide which one is more reliable.

Using a point model, the occupancy probability C_O of a cell with size $s \times s$ and with coordinates x, y is:

$$C_O(x, y) = \frac{\tau}{\sigma_x \sigma_y 2\pi} \int_{x-\frac{s}{2}}^{x+\frac{s}{2}} e^{-\frac{1}{2}\left(\frac{\xi-p_x}{\sigma_x}\right)^2} d\xi \int_{y-\frac{s}{2}}^{y+\frac{s}{2}} e^{-\frac{1}{2}\left(\frac{v-p_y}{\sigma_y}\right)^2} dv \quad (4)$$

The line model calculates the probability that a cell does not overlap with the line with length l . Hereby, the two end points of the line $p_y - \frac{l}{2}$ and $p_y + \frac{l}{2}$ are considered. The cell is free, if the line starting point is right from the cell or if the line ending point is left from the cell. Hence, the occupancy probability is calculated as a complementary probability. In detail, the occupancy probability C_O of a cell is calculated as follows:

$$C_O(x, y) = \left(\frac{1}{\sigma_x \sqrt{2\pi}} \int_{x-\frac{s}{2}}^{x+\frac{s}{2}} e^{-\frac{1}{2}\left(\frac{\xi-p_x}{\sigma_x}\right)^2} d\xi \right) \left(1 - \frac{1}{\sigma_y \sqrt{2\pi}} \int_{y+\frac{s}{2}}^{\infty} e^{-\frac{1}{2}\left(\frac{v-p_y+\frac{l}{2}}{\sigma_y}\right)^2} dv \right) \\ \left(1 - \frac{1}{\sigma_y \sqrt{2\pi}} \int_{-\infty}^{y-\frac{s}{2}} e^{-\frac{1}{2}\left(\frac{v-p_y-\frac{l}{2}}{\sigma_y}\right)^2} dv \right) \tau \quad (5)$$

All three models calculate the overlapping of a single measurement weighted with the reliability factor τ . This factor depends on the trust of the sensor itself and may be modified by measurement attributes like range or a quality factor.

Every cell contains a small ring buffer for measurements concerning this cell. In this ring buffer, every entry consists of a unique identifier id for the measurement and the weighted overlapping factor C_O or C_F . Fusing all measurements at this point to a single state is not advisable since it blurs information about dependencies to neighbour cells. Old measurements will be overwritten automatically if the ring buffer is full, so that there is an aging mechanism in this algorithm integrated.

6 Grid queries

An area from x_{min} and y_{min} to x_{max} and y_{max} with a set of cells Z has to be scanned in order to determine the state of the planned trajectory of the car.

$$X = \{x_{min}, x_{min} + s, x_{min} + 2s, \dots, x_{max}\} \quad (6)$$

$$Y = \{y_{min}, y_{min} + s, y_{min} + 2s, \dots, y_{max}\} \quad (7)$$

$$Z = X \times Y \quad (8)$$

All cells in the scanned area are combined by different measurements and tracks separately. Depending on the used model, different fusion algorithms are used for calculating the weighted overlapping of a measurement within the area.



Figure 2: Dynamically created free area without aging mechanism. Visible area is limited by two guard rails. Objects at the roads boundary reduces the free evidence

If the point model is used to define the position distribution, a common occupancy probability can be gained by simply adding all occupancy probabilities of all affected cells:

$$A_{O_{id}} = \sum_{x,y \in Z} C_{O_{id}}(x,y) \quad (9)$$

If the line model has been used, the occupancy probability of an area is calculated as follows:

$$A_{O_{id}} = C_{F_{id}}(x,y) \mid \max_{x,y \in Z} \quad (10)$$

Since we want to know if the whole scanned area is free, the cell with the minimum free probability is relevant for the free evidence for the whole set of cells.

$$A_{F_{id}} = C_{F_{id}}(x,y) \mid \min_{x,y \in Z} \quad (11)$$

As a result, a set of measurements is acquired containing one probability for each measurement: the existence probability of the measurement itself combined with the probability

that the measurement affects the scanned area assuming the correctness of the measurement.

The composition operation implicates dependent cell information caused by a single measurement. In contrast, several measurements are supposed to be independent. For every measured object or free area, a mass distribution can be provided based on A_O or A_F . It consists of four attributes "free", "occupied", "unknown" and "conflict".

$$m_O = A_O \quad (12)$$

$$m_F = A_F \quad (13)$$

$$m_U = 1 - m_F - m_O \quad (14)$$

$$m_C = 0 \quad (15)$$

To generate a final state for the queried area, all mass distributions are used as input values for Dezert-Smarandache-Theory (DSmT) [FS06]. In addition to Dempster-Shafer-Theory [YL08], this one is able to calculate a conflict value for two mass distributions.

Because the composition of contradicting mass distributions using DSmT is not commutative, all measurements for occupied areas are first composed to a single conflict-free mass distribution. A conflict-free mass distribution for free area measurements is calculated in the same way. These two mass distributions m_1 and m_2 are used for DSmT to calculate a final distribution m_{12} .

$$m_{12_O} = m_{1_O} \cdot m_{2_O} + m_{1_O} \cdot m_{2_U} + m_{1_U} \cdot m_{2_O} \quad (16)$$

$$m_{12_F} = m_{1_F} \cdot m_{2_F} + m_{1_F} \cdot m_{2_U} + m_{1_U} \cdot m_{2_F} \quad (17)$$

$$m_{12_U} = m_{1_U} \cdot m_{2_U} \quad (18)$$

$$m_{12_C} = m_{1_C} + m_{2_C} - m_{1_C} \cdot m_{2_C} + m_{1_O} \cdot m_{2_F} + m_{1_F} \cdot m_{1_O} \quad (19)$$

The final distribution can represent several scenarios for the queried area. The most common and simple state should be a high occupied mass or a high free mass representing an occupied or free area. If the unknown mass is high, it means that the set of measurements is insufficient to cover the selected area. A high conflict value means that there are contradicting information, so that no reliable statement can be done at this moment. In this situation the ratio between the free and occupied masses should be considered when a discrete decision is necessary.

7 Experimental results

For building the occupancy grid, a radar sensor and a laser sensor have been used. The internal object tracking of the radar sensor is based on a point model. Hence, the output

consists of objects with no width or length. Since the radar is able to measure the velocity of an object directly using Dopplers principle, static objects can be easily separated from dynamic objects.

A laser scanner provides a range of possible free areas for each ray. The sensor has an opening angle of 91 degree and provides data for ranges of at least 60 m.

To transform sensor data from the local car coordinate system to the global occupancy grid coordinate system, the relative positioning of the car is required. For this purpose, the angular velocity of every single wheel is measured. Together with wheel size and geometric configuration, it is possible to estimate the relative car position accurately.

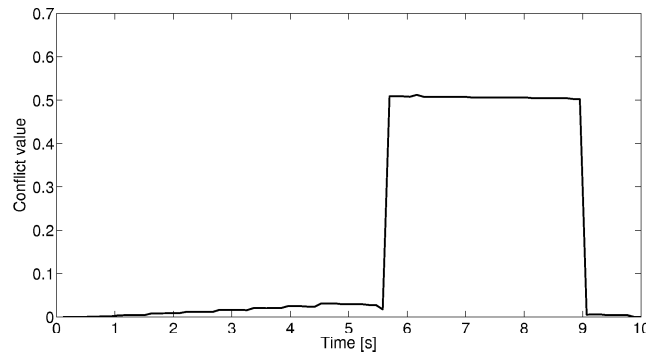


Figure 3: Conflict value when overdriving a ghost target (a metallic thermos flask)

The occupancy grid size in our experiment is $300 \text{ m} \times 300 \text{ m}$ with a cell size of $0.5 \text{ m} \times 0.5 \text{ m}$. Every cell has a ring buffer with space for 16 entries. The queried area is located in front of the car with a size of $6 \text{ m} \times 20 \text{ m}$ and represents the region of interest in the driving tube.

The software fulfills our real-time requirements since fusing of up to 20 point objects together with the free area in the specified configuration and querying the 120 m^2 region is done in less than 2 milliseconds on the target platform.

Test data sets show that the state of the queried area is mostly either fully free or fully occupied depending whether there is an object in the driving tube or not. For generating a data set with contradicting data, a metallic thermos flask lying on the ground has been used as a ghost target. It reflects the radar's radiation lobe causing a static object in the internal tracking. In contrast, the laser scanner does not detect the lying thermos flask since its height is too small to be hit by the laser ray.

Figure 3 shows the generated conflict value while overdriving the ghost target. The weighting factor τ has been set to 0.5 for both sensors.

8 Conclusion

This paper has introduced a new method for fusing several cells of an area together to a new state. All state information of each cell are marked in such a way that it is possible to reconstruct their dependencies or independencies. Virtually, all cells of an area are combined in such a way that it is equivalent to an area which consists of a large single cell. The result of this algorithm is approximately independent of the grid's cell size. In a nutshell, this approach is able to handle the dependencies of cell states correctly which is a requirement for good area query algorithms.

Since every cell contains a small ring buffer, the memory consumption of the grid is significantly larger compared to most other approaches. Adding a measurement to a cell can be done in constant time. However, when querying an area, the whole ring buffer of each cell in this area must be processed. Depending on the size of the area and the ring buffer, this step might be the most critical one if certain real time requirements must be fulfilled.

As an alternative algorithm, all measurements could also be stored in a ring buffer. A query algorithm calculates the intersection of these measurements with a polygon which may represent the driving tube. Approximately, the result is the same table as presented. Since there is no discretisation, this approach is more precise and has significant lower memory consumption depending on its ring buffer size. However, algorithms which are able to intersect concave polygons with gaussian blurred lines are more difficult to develop and they probably need much more computing time depending on the ring buffers size. From that point of view, the occupancy grid is an optimisation layer which offers a time-memory trade-off.

The occupancy grid only considers static objects or free areas. Dynamic objects only influence the visible area. Nevertheless, dynamic objects may also affect the trafficability of the driving tube. Further research is needed for integrating dynamic objects in the trafficability estimation.

In section 3 more sources for plausibility have been mentioned to optimize mass distribution of the area's state. These sources should also be integrated when estimating the existence of objects or free areas.

9 Acknowledgement

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