Information Maps: A Practical Approach to Position Dependent Parameterization

Benjamin Wilking, Daniel Meissner, Stephan Reuter, and Klaus Dietmayer
Institute of Measurement, Control, and Microtechnology
Ulm University, Germany
{benjamin.wilking, daniel.meissner, stephan.reuter, klaus.dietmayer}@uni-ulm.de

In this contribution a practical approach to determine and store position dependent parameters is presented. These parameters can be obtained, among others, using experimental results or expert knowledge and are stored in 'Information Maps'. Each Information Map can be interpreted as a kind of static grid map and the framework allows to link different maps hierarchically. The Information Maps can be local or global, with static and dynamic information in it. One application of Information Maps is the representation of position dependent characteristics of a sensor. Thus, for instance, it is feasible to store arbitrary attributes of a sensor's preprocessing in an Information Map and utilize them by simply taking the map value at the current position. This procedure is much more efficient than using the attributes of the sensor itself. Some examples where and how Information Maps can be used are presented in this publication. The Information Map is meant to be a simple and practical approach to the problem of position dependent parameterization in all kind of algorithms when the analytical description is not possible or can not be implemented efficiently.

Keywords: Information Maps; Parameterization; Sensor Analysis; Tracking; Context Information

1 Introduction

1.1 Motivation

Today, there are many different tasks to proceed in topics like advanced driver assistance systems or highly autonomous driving. These tasks can be e.g. sensor preprocessing including classification problems or multi-object tracking algorithms. There is a huge amount of different algorithms to solve all the challenging problems coming up with advanced assistance or autonomous systems. Coming along with all these algorithms is one widespread purpose: the parameterization. Obviously, the spatial resolution of common automotive sensors, like cameras, radars, and laser range finders decrease with the radial distance. But, especially algorithms for object detection highly depend on the sensors resolution. To model these dependencies as parameters analytically is not always possible. One of these parameters is the detection probability of every sensor in a multi-object tracking algorithm. If this parameter is not modeled correctly, it might happen, that information about an object from different sensors is ambiguous, e.g. a new track is initialized based on the measurement of one sensor, but a second sensor has no information about the new object. Because of this ambiguity, the track might be deleted again. Another example for the importance of modeling sensors is surround tracking for autonomous driving functions. It is not always possible to have sensors all around the own vehicle to observe the complete surround-
But the information maps are not limited in a sensor independent way to handle multi-sensor fusion. The Information Map is a generic and sensor independent approach to use 'Information Maps' to store parameters. Other examples where useful, position dependent knowledge can be stored in maps are the a priori class probabilities of an Bayesian classifier (see Section 4) and the maximum search radius of a clustering algorithm in 2D, etcetera.

1.3 Related work

Modeling the detection probability using a map was already done in different publications. One of them is [8], in which the detection probability was modeled using an occupancy grid map in a static scenario. Two laser range finders are used to generate measurements and the detection probability dynamically depends on the occlusions in the scene. The basic idea to use a map to determine detection probabilities is quite similar to this contribution, but modeling the environment in different maps, like global or local/sensory, or with linked maps even including context information is not done in [8]. Another approach to solve occlusions using the detection probability was presented from [4]. Therein a method was presented to create a detection probability map built by convolving the target position and a width function. The main task of [4] is the same as in [8], but incorporating the actual object dimensions and its uncertainties. This contribution does not compare to the way of modeling detection probabilities presented in [4]. In fact, the presented approach here allows to combine the information obtained from [4] with other sources. Further related work can be found in [4].

This contribution is organized as follows: First, the 'Information Map' approach is explained in detail. Afterwards, a method to create static maps is presented, with a focus on detection probabilities for multi-object trackers. An excursion to how context information can be incorporated using Information Maps is followed by a short conclusion.

2 Information Map

As already mentioned, this contribution proposes to use 'Information Maps' to store parameters. Therefore, the determined parameters are not continuous functions: they are discretized and stored as a kind of grid map. To do that, these maps are represented as large matrices. A easy way to work with matrices fast and effec-

\[
v(x_{k|k-1}) = \int p_S(x_{k-1})p(x_{k|k-1}|x_{k-1})v(x_{k-1})dx_{k-1} + b_{k-1}(x),
\]

\[
v(x_k) = [1 - p_D(x)]v(x_{k|k-1}) + 
\sum_{z \in Z_k} \lambda_{x}(z) + \int p_D(\xi)p(z|\xi)v(\xi_{k|k-1})d\xi.
\]
every map needs to know its own resolution and the origin of the local system in map coordinates (rows, columns) as shown for the tracking example in Fig. 1. The only limitation here is that the data is stored as a matrix. Thus it is also possible to save parameters in non Cartesian coordinates like the polar coordinate system. It is also necessary to differ between local and global maps. Referring to the tracking example, this means that every sensor can have its own local map for a certain tracking parameter. But sometimes it is also useful to have a global map incorporating all sensor specific information. In this context global means that the map is located at the origin of the tracking system like local/sensory maps, but it is valid for the complete system rather than limited to only one sensor. Short example: Two sensors observe an area with an occlusion. This occlusion is modeled using an Information Map. Tracking objects in the observed area suffers from the occlusion and the resulting track loss. If there is the knowledge, that the object crossing the occlusion can not disappear, the persistence probability in the area of occlusion can kept high.

With that model using a combined global map from both sensors and the occlusion map the track will survive when crossing the occluded area (Fig. 2). In other cases, it is useful to have only one global and no local ones. Another property of Information Maps is the possibility of a hierarchical request. This means, that multiple maps can be linked together in an hierarchical manner. If there is an information request to a certain Information Map, the map does not only return it’s own information, but the combined information of itself and all it’s appended maps. An example for an hierarchical request is shown in Fig. 3. Further, every map can be regarded as kind of interface between the matrix the information is stored in and the application which requests the information. Thus, an information map can also be an interface to other toolboxes and information sources like a dynamic grid map. Therefor, it is not necessary to extract the information from the source and save it into a new matrix. The Information Map only gets a position in local coordinates and delivers the result combining all appended Information Maps at this position.

Knowledge about the static behavior around the system is only half of the medal. In many cases it is also necessary to know something
Figure 3: Example of a hierarchical request to get a birth probability at the position of a certain measurement. First the birth probability is requested from the static local/sensory Birth Probability Map a). This map forwards the request to a global dynamic Object Map b), where all dynamic objects were inserted, and to any other Information Map appended c). In a last step the values from all maps are combined and the result is returned.

3 Creating static sensory maps

One big advantage of using Information Maps containing the attributes of a sensor is the possibility to determine the perception performance of the preprocessing of this sensor. These attributes are needed very often, but in most cases, these attributes are not known or wrongly assumed. This problem can be explained by a simple example using laser range finders: The laser range finder has a huge perception range and a relatively wide opening angle. But normally not the laser detections itself are used as measurements. In case of detecting vehicles, a preprocessing algorithm as described in [6], where a box is fitted into the data of the laser range finder, can be used. But fitting boxes into data depends on the angular resolution of the laser scanner. Objects in a higher distance have fewer points than objects close to the range finder. Therefore the preprocessing has attributes completely different to those of the sensor itself. A further problem occurs when combining sensors in a preprocessing step. The opening angle and range can’t be determined anymore, when using multiple sensors as one ‘virtual’ sensor. Fig. 3a shows an example where three laser range finders are mounted at three different positions at the front of a car. The data of all three range finders are transformed into the vehicle coordinate system and are used for the box fitting algorithm. Now there is one single ‘virtual’ sensor and therefore the need to know the attributes of this new sensor, respectively it’s preprocessing, arises.

A good way to create a new map for a certain parameter is to analyze the preprocessing over time, which is illustrated by the following example: creating a static map for the detection probability of the ‘virtual’ sensor from above can be done as follows: after recording multiple or long sequences in different environments, e.g. motorway, country road, city, and so on, all detections, if possible true positives only, are plotted in one image (Fig. 4b). With that plot the perception range can be estimated. If ground truth data is available the percentage of detected vehicles, the detection probability, can be calculated for every cell of the map. In most cases it is not possible to calculate the complete map because the training data normally is not sufficient or there is no ground truth data available. Thus expert knowledge is needed to create the final map from the plotted data. A very practical approach for that is to use a simple image editing tool and to save the map in a standard image format. The benefit is that this map can easily be edited and afterwards it is very simple to load such an image as an Information Map using e.g. OpenCV [2]. The result after incorporating the expert knowledge can be seen in Fig. 4c. The very low detection probability right in front of the vehicle is caused by bad results of the box fit when the detected object is to close to the own vehicle. If ground truth data for the true positives is available it is also possible to determine the measurement uncertainty at every position and an ‘Uncertainty Map’ for the sensor as well as a ‘Clutter Map’ can be created. Such maps do not have to follow any probability distribution. Thus, it is possible to depict nearly every distribution for most sensors. After creating a static Detection Map it can be combined e.g. with the...
Figure 4: Scenario with three laser range finders mounted at the front of a vehicle. a) The mounting positions of the sensors. b) The measurements of the preprocessing, combining all three sensors in one virtual sensor. c) The resulting Detection Map.

Dynamic detection probability from [4]. When using a sensor with measurements which can’t be transformed into the vehicle coordinates, e.g. a camera, special a priori knowledge is needed. In case of a camera a video classifier like the Viola-Jones cascade [12] can be used to detect vehicles. The transformation of the measurements into vehicle coordinates can be done assuming that the size of the objects is known or with the knowledge that the world around the vehicle conforms to the flat world assumption. This is necessary because of the loss of information in the third dimension, when projecting the 3D world to a 2D image. For the camera it is now possible to create a \( p_D \) map in the same way as described for the laser range finders. It is often assumed that the field of view is equal to the opening angle of the camera and the range is limited by the minimum size of a detection in pixels. But regarding that measurements created by a detector do not depend on the camera itself, but rather on the preprocessing, it is a better way to use the attributes of the preprocessing instead of the attributes of the camera itself.

4 Context Information

Among others, contextual information can be a dynamic grid map where static objects are detected. In [7] an approach to incorporate this information in the preprocessing step of the sensors is proposed, but the same approach could also be used to improve the tracking directly, using the Information Map as interface to detection or birth probability. In case of static setups, e.g. intelligent infrastructure, most of the contextual information like traffic lanes, sidewalks and much more are static as well. In this case, it is a very practical approach to store context information in a static map. One example for such an intelligent infrastructure provides the Ko-PER project, which is part of research initiative Ko-FAS [1], where a major intersection was equipped with a network of laser range finders and mono cameras [3] (see Fig. 5). If a bird eye image or a digital map of this intersection is available, an Information Map can be used to incorporate context information. At this intersection, one problem of the tracking using laser range finders is to initialize new tracks with a correct orientation angle, because the obtained box-measurements using a box-fit have very uncertain information about the orientation. Us-
ing an image editing tool, the image of the intersection can be painted in different colors, where one color matches one initial orientation. Using this information about the initial orientation when instantiating a new track improves the initialization time and precision of the tracks. Another example at this intersection is the classification of objects using a Bayes classifier, where the a priori class probability can be stored in an Information Map equivalent to Fig. 6. Here the position dependent a priori class probability Information Map for vehicles at the Ko-FAS intersection (Fig. 5) is depicted. The map shows brighter colors where the class probabilities are higher. That corresponds to high class probabilities in the areas of the streets where most of the road users are vehicles. The probability declines at the curbside and is low at the sidewalks. For each distinguished road user class a map like in Fig. 6 is needed and the map values of one position have to sum to one. Even the maximum search radius for a grid based DBSCAN algorithm [9] can be stored as a Map. Further, the same approach can be used in dynamic scenarios using the Information Map as an interface to digital maps or a databases.

5 Conclusion

In this contribution Information Maps are presented as a practical approach to determine and store position dependent parameters. They are an alternative tool to combine information from different sources without using complex analytical descriptions. As shown, the Information Map can be used to provide information about parameters in space, context, as well as a priori knowledge. With our approach it is possible to evaluate certain parameters, like the detection probability of a sensor, in experiments. These experiments can easily be extended by expert knowledge and therefore can lead to better performances. Using Information Maps instead of an analytical description does not improve the results necessarily. The convenient parameter representation and the efficient parameter access are the main advantages of the proposed Information Maps. Especially in case where no analytical description of the parameters is feasible, like the a priori class probability at intersections, the benefit of 2D representation of parameters using the Information Maps becomes apparent.

References

[1] Forschungsinitiative Ko-FAS. http://www.ko-fas.de, 7 2012.
[2] G. Bradski. The OpenCV Library. Dr. Dobb’s Journal of Software Tools, 2000.
[3] Michael Goldhammer, Elias Strigel, Daniel Meissner, Ulrich Brunsmann, Konrad Doll, and Klaus Dietmayer. Cooperative multi sensor network for traffic safety applications at intersections. In 15th International IEEE Conference on Intelligent Transportation Systems, pages 1178–1183, 9 2012.
[4] L. Lamard, R. Chapuis, and J.-P. Boyer. Dealing with occlusions with multi targets tracking algorithms for the real road context. In IEEE Intelligent Vehicles Symposium (IV), pages 371–376, 2012.
[5] Ronald Mahler. Statistical Multisource-Multitarget Information Fusion. Artech House Inc., Norwood, 2007.
[6] Michael Munz, Klaus Dietmayer, and Mirko Mählisch. A sensor independent probabilistic fusion system for driver assistance systems. In Proceedings of the 12th International IEEE Conference on Intelligent Transportation Systems, St. Louis, MO, USA, 2009.
[7] Dominik Nuss, Stephan Reuter, Marcus Konrad, Michael Munz, and Klaus Dietmayer. Using grid maps to reduce the number of false positive measurements in advanced driver assistance systems. In 15th
International IEEE Conference on Intelligent Transportation Systems (ITSC), pages 1509–1514, 9 2012.

[8] Stephan Reuter and Klaus Dietmayer. Pedestrian tracking using random finite sets. In Proceedings of the 14th International Conference on Information Fusion, pages 1–8, 2011.

[9] Stephan Reuter, Daniel Meissner, and Klaus Dietmayer. Multi-object tracking at intersections using the cardinalized probability hypothesis density filter. In 15th International IEEE Conference on Intelligent Transportation Systems, pages 1172–1177, 9 2012.

[10] Conrad Sanderson. Armadillo: An open source c++ linear algebra library for fast prototyping and computationally intensive experiments. Technical report, NICTA, 2010.

[11] Sebastian Thrun, Wolfram Burgard, and Dieter Fox. Probabilistic Robotics (Intelligent Robotics and Autonomous Agents). The MIT Press, 2005.

[12] P. Viola and M. Jones. Rapid object detection using a boosted cascade of simple features. In Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), volume 1, pages I–511 – I–518 vol.1, 2001.

[13] Thorsten Weiss and Klaus Dietmayer. Applications for driver assistant systems using online maps. In Proceedings of the International Workshop on Intelligent Transportation, 2008.