

Unsupervised Texture Segmentation for 2D Probabilistic Occupancy Maps

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Abstract – This paper presents a novel method for the segmentation of probabilistic two-dimensional occupancy maps, based on the analysis of their texture characteristics. The texture is represented by means of a double distribution of “Local Binary Pattern” and “Contrast”. The logarithmic likelihood ratio, *G*-statistic, is used to measure the degree of similarity between different regions; this pseudo metric measure compares *LBP/C* distributions linked to different segments. The innovative algorithm is used to segment the probabilistic images in regions that characterize the space according to the certainty of its occupancy level. For a better interaction between an autonomous system and its environment, the segmentation scheme is also able to differentiate between objects present in the scene by analyzing the proximity between occupied segments. Along with experimental results, a comparison with other algorithms is provided in order to demonstrate the efficiency of the proposed approach.

Keywords – segmentation, probabilistic maps, local binary pattern, contrast, texture.

I. INTRODUCTION

This research work constitutes a bridge between two relatively complex domains: the representation of probabilistic images and their segmentation. The development of segmentation approaches for probabilistic maps is innovative since very few researches have dealt with applications on this specific type of images. In addition to the fuzziness of texture distribution which increases considerably the degree of complexity, no consensus is currently established concerning the representation of probabilistic images. Heterogeneity in the representation implies that each model is treated on a purely individual basis and methods of extrapolations are necessary in order to generalize the concepts which have been validated on a particular scheme. The third complication arises with the fact that existing segmentation methods are extremely specialized as they generally treat only one preset type of images. This makes the process of extrapolation to cover the case of probabilistic images more laborious.

Segmentation algorithms try to classify the pixels of an image based on their properties and their relationship with

their entourage. Thereafter the goal of the segmentation is to divide an image into areas characterized by homogeneous properties. Several segmentation approaches have been proposed in the literature, these methods can be classified either as region-based, boundary-based or as a combination of the two. In addition the segmentation is either supervised or unsupervised. Unsupervised segmentation is applied in the case where, a priori, no information concerning the contents or the textures which characterize the image, is available. Approaches based on classical methods such as split and merge [1], pyramid node linking [2, 3], as well as the quad-trees [4] for the combination of statistical and spatial data, were the first to treat the unsupervised region-based segmentation. Recent segmentation methods explore, on one hand multi-resolution filtering, using Gabor filters [5, 6, 7] or the wavelets [8, 9], and on the other hand statistics with hidden Markov fields [10, 11].

This research work being performed in the context of autonomous mobile robotic exploration in cluttered environments, the value associated with each cell in a probabilistic map corresponds to the probability of this cell being occupied. Therefore, region-based segmentation appears to be well suited to ensure obstacle detection and allow shape recognition. Indeed the explored space is characterized by a series of edges corresponding to the rays emitted by an active range sensor used to monitor space occupancy. The combination of contrast and texture measures reveals to be an appropriate strategy for differentiating between segments present in probabilistic images.

The work of Ojala *et al.* [12, 13, 14] on “Local Binary Pattern” and “Contrast” (*LBP/C*) segmentation explores these concepts on images with sharp patterns. However, the major problem with the segmentation of probabilistic images comes from the fact that transitions between free and occupied spaces do not define clear boundaries and are spread out according to the margin of error introduced by the sensor model. The present work proposes a refinement to the original *LBP/C* segmentation mechanism to handle smooth transitions in complex images while achieving accurate contours definition.

The following section introduces the concept of probabilistic occupancy grids which constitute the basis of probabilistic imaging. Next the double distribution of "Local Binary Pattern" and "Contrast" used to describe textures is reviewed. Then the proposed segmentation technique is detailed before experimental results and potential applications are discussed.

II. PROBABILISTIC OCCUPANCY GRIDS

In the context of space mapping with uncertainty for autonomous robotics, probabilistic images are the representation of occupancy grids. This approach was mainly developed by Alberto Elfes [15, 16, 17] and incorporates notions from areas such as probability theory, optimal estimation, random field models and decision theory. Elfes [17] defines the occupancy grid representation as a multi-dimensional random field model that maintains stochastic estimates of the occupancy state of each cell in the environment, symbolized by a spatial lattice. The number of relevant additions which were carried out thereafter is limited.

Generally, in order to build a representation of its space from sensors data, a robot must estimate the state of the cells by analyzing the acquired range information. The interpretation step is carried out using the probabilistic models of the sensors. So as to allow an incremental update of the occupancy grid, several methods of data fusion were developed, they are able to combine readings relative to various sensors and points of view. Fusion methods [18] include Probability Theory [19], Dempster-Shafer or Evidence Theory, Fuzzy Sets, and various *ad hoc* methods used in Artificial Intelligence [17].

The combination of data resulting from various occupancy grids obtained using various sensors (such as sonars and laser range sensors), has various advantages [16]. In the first place, if the model is well designed, the representation can exploit the complementarity of the space coverage as well as the strengths of each sensor, which can increase considerably the fault tolerance of the global system. Second, since the probabilistic occupancy grids represent the data on a common basis, no matter their source, their processing is simplified and homogenized. In third place, each sensor can be treated in a modular way, and probabilistic grids are built for each of them. At the end, the intermediate representations are merged to represent the environment. Finally, the probabilistic occupancy grids make possible to take into account various levels of precision in the representation of the sensor's measurements and uncertainty in the position of a moving robot. This uncertainty is modeled in [15] by a Gaussian function which clouds the current grids.

III. TEXTURE REPRESENTATION

As proposed in [12], region content can be described by a multi-variable distribution consisting of the "Local Binary Pattern" (*LBP*) and the "Contrast" (*C*). For each pixel in a given region of the original image, a block of [3x3] pixels is considered (Fig. 1a). In order to obtain a binary representation, the central pixel is applied as a threshold on the neighboring ones. The pixels that have a value equal or higher to that of the central pixel are set to one, the others to zero (Fig. 1b). Thereafter, these binary values are multiplied by binomial weights (Fig. 1c), and the values obtained (Fig. 1d) are added in order to define the *LBP* value of the texture unit. In parallel, the "Contrast" (*C*) value for a given pixel is equal to the difference between the average values of the pixels in the block of size [3x3] having a binary value of one and those having a binary value of zero.

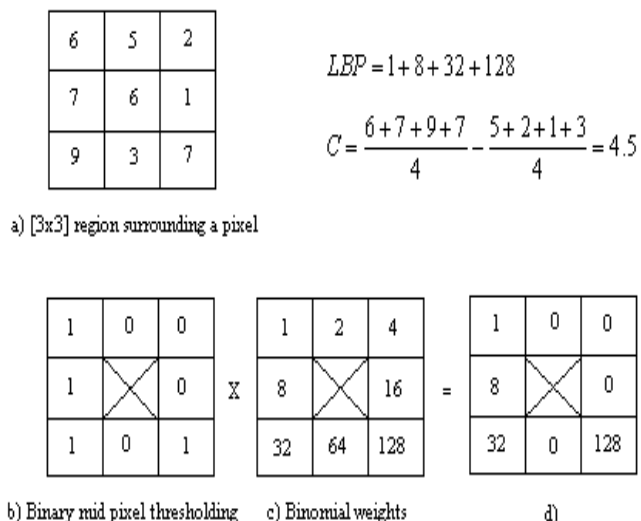


Fig. 1. Evaluation of the *LBP* and *C* values for a texture unit.

The *C* measure is meant to complement that of *LBP* since the latter describes only the spatial structure of the local textures without taking into account the intensity difference. The value of the *LBP* parameter varies theoretically between 0 and 255 for a total of 256 possible values. As for *C*, its value is decimal and is bounded in the interval spreading from -254 to 255. These ranges presuppose a representation of the pixel values on eight bits. Thereafter, in order to limit the number of values that the contrast can take and speed up the classification procedure, a discretization process is carried out in which *C* is mapped to *b* possible integer values (e.g. if *C* = -254, it is represented by 0, and if it is equal to 255, by *b*).

In a given region, once the (*LBP*, *C*) pair is calculated for each pixel, a three-dimensional histogram of size [256 (*LBP*)

$\times b$ (C) \times number pixels characterized by a specific *LBP/C* pair] representing the distribution is computed. The selection of a proper number of bins, b , for the ‘‘Contrast’’ values remains a compromise between precision and performance.

Although Ojala *et al.* [12] did not observe significant difference in performance between 8 and 16 bins, our experiments have shown that a value of 8 provides a better ratio between precision and performance, and thus it is used in our implementation.

In order to classify map segments, the logarithmic likelihood ratio, the G -statistic [20], is used to compare two histograms of *LBP/C* distributions. The value of G indicates the probability that two distributions have the same population as origin. In other words, it specifies the likelihood that two regions have similar textures and contrasts, and make up a single segment. The larger is the G -statistic value, the less would be the odds in the segmentation. This measurement of similarity is calculated as follows:

$$G = 2 \left[\sum_{s,m} \sum_{i=1}^n f_i \times \log(f_i) \right] - 2 \left[\sum_{s,m} \left(\sum_{i=1}^n f_i \right) \times \log \left(\sum_{i=1}^n f_i \right) \right] - 2 \left[\sum_{i=1}^n \left(\sum_{s,m} f_i \right) \times \log \left(\sum_{s,m} f_i \right) \right] + 2 \left[\left(\sum_{s,m} \sum_{i=1}^n f_i \right) \times \log \left(\sum_{s,m} \sum_{i=1}^n f_i \right) \right] \quad (1)$$

where f_i corresponds to the number of pixels characterized by a pair of *LBP/C* values in bin i . s and m represent the two distributions to compare and n is the number of bins in each of the analyzed histograms.

IV. SEGMENTATION ALGORITHM

In a similar way to the approach introduced by Ojala *et al.* [12], the proposed segmentation algorithm can be divided in three phases. That is the hierarchical division, the segments creation and the refinement step. The first phase of the proposed method is similar to that of the algorithm proposed in [12]. The innovation in the proposed scheme mainly comes from major changes introduced into the second and third stages. These modifications not only adapt and optimize the original algorithm to handle probabilistic images, but also significantly reduce computation time.

The first phase divides the image into areas characterized by roughly uniform textures. Thereafter the segments creation step combines similar adjacent regions into segments. At this level the segments only approximate the various regions present in the image, the refinement stage is applied to increase the accuracy on contours localization.

A. Hierarchical Division

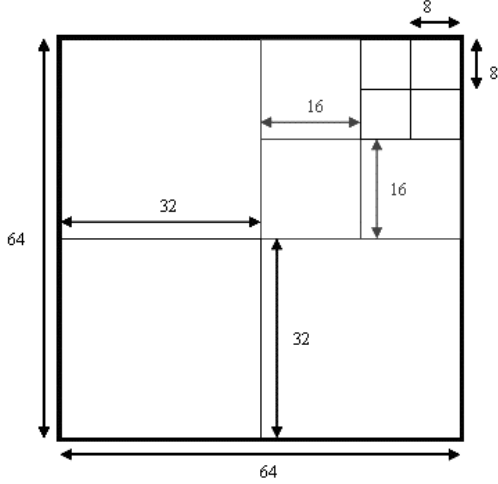
This phase hierarchically subdivides the original image into square blocks of variable sizes but of relatively uniform textures.

A uniformity test has been developed to determine if a given parent region contains heterogeneous textures and therefore must be subdivided into four sub-regions of equal size. The procedure starts by identifying the four sub-regions and calculating the logarithmic likelihood ratio between each of the six possible pairs. The largest and the smallest G -statistic values, eq. (1), denoted respectively by G_{max} and G_{min} , are identified among those pairs. The parent block is considered non-uniform and thus subdivided if the relative difference between G_{max} and G_{min} is higher than a certain threshold designated by X :

$$R = \frac{G_{max}}{G_{min}} > X \quad (2)$$

Experimentation demonstrated that a relatively low value of X provides better end results given that supplementary subdivisions that do not segment regions with strong distinctive features can easily be corrected in the second phase. On the opposite, segments missed in the first phase cannot be introduced afterwards. An over-segmentation is therefore privileged in this early phase. In the case of 2D probabilistic maps, a choice of $X=1.2$ performed well, since 20% of difference between G_{max} and G_{min} indicated a perceptible deviation in the region’s local texture.

The hierarchical division phase starts by subdividing the probabilistic image into blocks of size S_{max} , whose value is [64x64] pixels. For each of the blocks, the decision to operate a first level of subdivision depends on the result of the uniformity test introduced above. If the test’s result is positive for a given block, four sub-blocks of size [32x32] each are obtained. In this case, each of these is submitted to the uniformity test which decides if a second level of subdivision is necessary. The subdivision process continues iteratively until a stopping condition is met. The minimum size, S_{min} , that a sub-region size can reach was chosen as a criterion. Ojala *et al.* claim in [12] that two levels of subdivision are sufficient and provide an adequate segmentation final result, but our experiments showed that a third level, leading to a value of [8x8] for S_{min} , is necessary in the case of the probabilistic images. Fig. 2 illustrates the recursive subdivision process. Despite the computational overhead that is added by this supplementary step, the final phase is relieved from a costly classification burden, and better segmentation results are achieved.



$$\begin{aligned}
 &\text{if } \left(R^{64} = \frac{G_{\max}^{32}}{G_{\min}^{32}} \geq 1.2 \right) \text{ then divide into 4 sub-blocks of } [32 \times 32] \\
 &\Rightarrow \text{if } \left(R^{32} = \frac{G_{\max}^{16}}{G_{\min}^{16}} \geq 1.2 \right) \text{ then divide into 4 sub-blocks of } [16 \times 16] \\
 &\implies \text{if } \left(R^{16} = \frac{G_{\max}^8}{G_{\min}^8} \geq 1.2 \right) \text{ then divide into 4 sub-blocks of } [8 \times 8]
 \end{aligned}$$

Fig. 2. Representation of the subdivision scheme.

B. Segments Creation

This phase aims at merging similar neighboring regions until a convergence criterion is met. Mainly, fusion involves adjacent blocks characterized by an average Occupancy Probability, OP , which is in the same range. This parameter, defined as the average pixels intensity level in a region R_i of size $[N \times M]$, is determined using the following equation:

$$OP_i = \frac{1}{M \cdot N} \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} I(r_{k,l}) \mid r_{k,l} \in R_i \quad (3)$$

The choice of the OP parameter, used to evaluate texture similarity between adjacent regions, is related to the structure of the probabilistic occupancy grid in which pixel values correspond to the probability of space occupancy. After normalizing the pixels' values in the range $[0;1]$, if a region is totally unknown it will be characterized by an OP of 0.5; if the region was scanned by the range sensor mounted on a mobile vehicle, two possibilities exist: the first one generates an OP below 0.5 and corresponds to the case where the region of space is mostly free; the second produces an OP higher than 0.5 and involves a region of space which is mostly occupied.

For the purpose of safe robot navigation, the probabilistic map can then be segmented into regions characterized by deterministic states, S , that is $S(R_i) \in \{free, unknown, occupied\}$. These fall respectively in the following ranges of OP 's values: $[0;0.5[$, $[0.5]$ and $]0.5;1]$. Following this

evaluation, if a group of adjacent regions have OP s in the same range, they are merged together and are classified as a segment with a uniform occupancy level. On the other hand, if two different segments with OP values in the same range, are not adjacent in space, they are kept as two separate objects to avoid confusion in objects recognition.

C. Refinement

In this last phase, segmentation results are refined by reclassifying the pixels located on the edge between two adjacent regions. If the hierarchical division and segments creation phases were successful, the segmentation results at this stage should already be coherent, but the level of precision on the localization of segments' contours can still be improved by this refinement procedure.

The refinement step is based on the fact that the range of OP values leading to an unknown segment classification is very narrow and is limited to a single value $[0.5]$. Even if a segment overlaps between an unknown space and a known one (free or occupied) by a limited number of pixels, it will still be considered as known by the segments creation phase. Therefore, the space whose occupancy is known always juts out into the unknown one. A process of compaction must be applied to the free and occupied segments in order to delimit them well and to expand the unknown ones. At the implementation level, this process consists of scanning the probabilistic image from each of the four possible sides: right-left, left-right, bottom-top and top-bottom. In each of the scans, when a boundary between an unknown and a known space is found, pixels of the known space which have a value of 0.5 are reclassified as belonging to the unknown region, until a pixel whose value is different is met. The four sides scanning procedure ensures coverage of all possible boundary shapes.

The refinement step implements this compaction process between the free/occupied segments and the unknown segments adjacent to them. Since free and occupied spaces do not define clear boundaries and are spread out according to the margin of error introduced by the sensor model, the application of a similar compaction process cannot improve the segmentation result between the two types of known spaces and thus adjacent free/occupied segments are not concerned by this step.

V. EXPERIMENTAL RESULTS

In this section, segmentation results on three probabilistic images each of size $[320 \times 320]$ are presented. These images are obtained using a laser range finder simulator for 2D surface mapping that was developed in previous work [18]. Occupied spaces' shape as well as the number and position of the range sensor's points of view differ from an image to another. In Fig. 3a, 4a and 5a, white pixels represent the

surface of objects, dark pixels correspond to free space, and intermediate grayscale pixels map unexplored areas. The first image (Fig. 3a) contains an object resembling an electrical plug, while the objects used in the following images (Fig. 4a and 5a) have a rectangular shape. Three range sensor scans are taken with Gaussian error ($\sigma^2=25$) on the range measurements and merged to build the probabilistic maps shown in Fig. 3a and 4a, while four scans are used in Fig. 5a. The step angle between two adjacent sensor's rays which defines the resolution is fixed to 1 degree in all generated images.

The parameters used in the segmentation technique's implementation are the same as the ones described in the preceding sections. In the hierarchical division phase, the

size of the first level of subdivided blocks, S_{max} is $[64 \times 64]$, and three subdivision levels are conducted, leading to a S_{min} of $[8 \times 8]$. Fig. 3b, 4b and 5b present the results of the hierarchical division phase of the algorithm, while Fig. 3c, 4c and 5c show the segmented maps after the segments creation phase. The segments obtained at the end of the second step approximate well the shape of the regions present in the probabilistic images; nevertheless, some isolated regions are generated. These originate from the absence of range measurements from certain points of view materialized by an insufficient exploration of the environment, especially where complicated objects are used, such as in Fig. 3. The rough localization of contours between free and unknown space is also obvious.

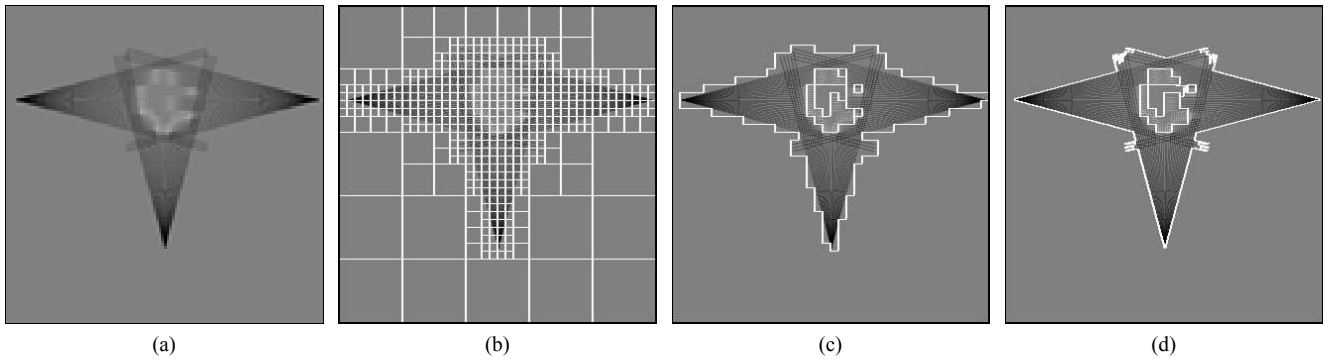


Fig. 3. Probabilistic map segmentation on a complex object.

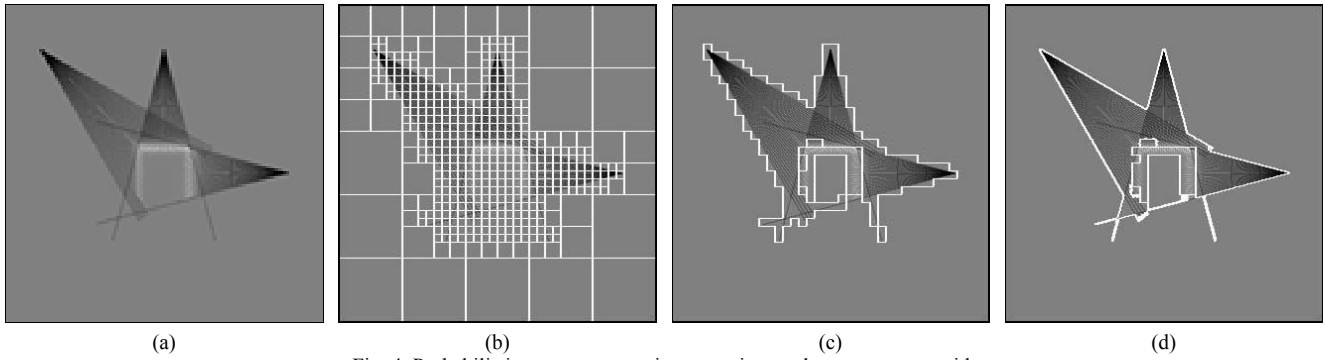


Fig. 4. Probabilistic map segmentation on an incomplete occupancy grid.

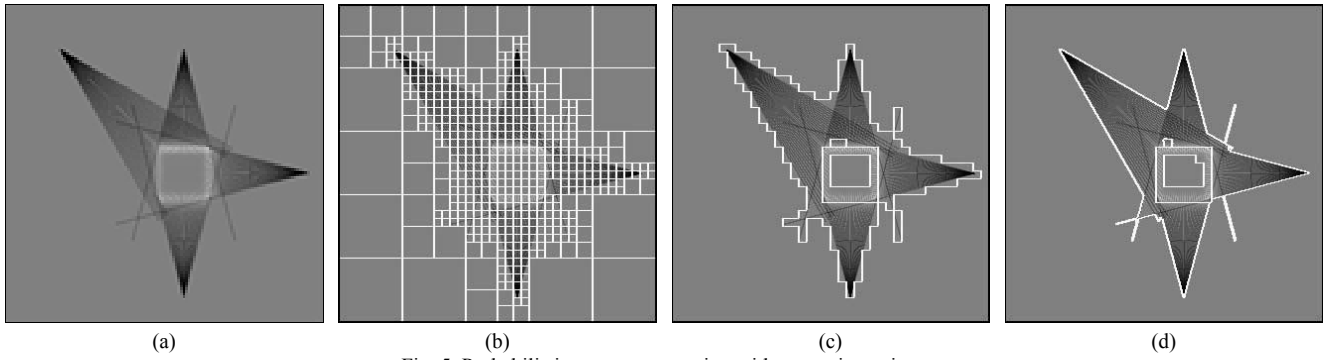


Fig. 5. Probabilistic map segmentation with extra viewpoints.

Segmentation results obtained after the refinement phase are showed in Fig. 3d, 4d and 5d respectively for the three probabilistic images. Important improvement on contours definition is achieved and isolated regions are removed as they get merged with the corresponding areas

From a qualitative point of view, segmentation results obtained with the proposed approach advantageously compare with those obtained by Ojala *et al.* [12]. The technique can be directly used for applications such as path planning, collision avoidance and interaction control for a mobile robot navigating in an unknown environment mapped by sensors with high uncertainty level. From a quantitative point of view, the proposed algorithm is also computationally efficient. The segmentation process takes between 35 and 40 seconds for a [320 x 320] probabilistic image when running on Matlab 7.0. Compared with the implementation that we have realized of the algorithm proposed in [12], the proposed scheme leads to more accurate segmentation and performs more than a hundred times faster.

VI. CONCLUSION

This paper proposes a refined unsupervised segmentation algorithm for two-dimensional probabilistic occupancy maps. The method is based on the comparison for two given regions, between the distributions of local texture characteristics termed in function of “Local Binary Pattern” and “Contrast”. The segmentation technique leads to the creation of homogeneous texture regions, which characterize the environment according to its occupancy level. The region-based algorithm corresponds to an adapted and improved version of the approach proposed in [12]. The first two phases split the original image in segments whose shape approximate the regions present in the image. Subsequently the refinement step achieves a high level of convergence between the segmented areas and the real physical model. Smooth transition zones between regions of various occupancy levels that make classical segmentation techniques fail on probabilistic maps are efficiently handled to classify pixels on the proper side of the edges.

The new method proved to be effective and efficient in the case of probabilistic images constructed by means of a laser range sensor. Since the probabilistic environment is characterized by areas with relatively uniform texture, regions can be linked to create segments having similar occupancy level.

This work provides a strong basis for our research on robot guidance from probabilistic models. Segmented probabilistic maps are now being used to optimize mobile platforms navigation in uncertain environments. This approach is also being extended for the segmentation of three-dimensional probabilistic environment models.

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