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Application of Segmented 2D Probabilistic Occupancy Maps for Mobile Robot Sensing and Navigation

Bassel Abou Merhy, Pierre Payeur, Emil M. Petriu
School of Information Technology and Engineering
University of Ottawa
Ottawa, ON, Canada, K1N 6N5
[bassel, ppayeur, petriu]@site.uottawa.ca

Abstract *– The concepts of occupancy grids and probabilistic maps were introduced at the end of the eighties. Since then, research work focussed mainly on the definition of the representation, data fusion and generation of occupancy models. Few consideration has been given to processing occupancy maps as textured images in order to extract meaningful information required for robot navigation and control of interactions with the environment. This paper investigates the application of segmentation techniques on probabilistic occupancy maps represented as textured images. Enhancements are proposed to a uniformity estimation technique based on local binary pattern and contrast (LBP/C) to achieve robust segmentation of occupancy maps that typically result from range sensors with limited resolution. The accuracy of the segmented 2D occupancy maps is demonstrated experimentally through an application on mobile robot navigation with collision avoidance.*

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

I. INTRODUCTION

Navigating mobile robots from occupancy maps permitted the development of very efficient platforms while keeping the amount of processing at a relatively low level. However, most occupancy maps discussed in the literature ensure perfectly reliable knowledge about the state of the robot workspace, that is, areas are either empty, occupied or have not been explored. Applying this type of maps for safe robot navigation with autonomous perception capabilities implies that regions are scanned without any gap between the viewpoints and that sensors are perfectly calibrated. The use of probabilistic occupancy maps alleviates these constraints by encoding uncertainties directly into the maps. On the other hand, identification of secure areas for the mobile robot to circulate is made more difficult as maps no longer show uniformity and sharp transitions. This paper extends an innovative segmentation approach for applications where a mobile robot must navigate around obstacles located with uncertainty in a map obtained from a range finder that only provides partial coverage of space.

Probabilistic occupancy maps are characterized by the fuzziness of texture distribution which increases considerably the degree of complexity in comparison with standard deterministic representations. In spite of a wide interest in this type of mapping, no consensus is yet established about the representation of probabilistic images. Heterogeneity in the representation implies that each model is treated on a purely individual basis and methods of extrapolation are necessary in order to generalize the concepts which have been validated on a particular scheme. Complication also arises from the fact that existing segmentation methods are extremely specialized as they generally treat only one preset type of images. Extrapolation of classical segmentation techniques to cover the case of probabilistic images is therefore more laborious.

Typically, segmentation algorithms try to classify the pixels of an image based on their properties and their relationship with their entourage. Thereafter the goal of segmentation is to divide an image into areas characterized by homogeneous properties. Several segmentation approaches have been proposed in the literature that can be classified either as region-based, boundary-based or as a combination of the two. In addition, segmentation is either supervised or unsupervised. Unsupervised segmentation is applied in cases where no *a priori* information about the contents or the textures of the image is available. Approaches based on classical methods such as split and merge [1], pyramid node linking [2, 3], as well as quadtrees [4] for the combination of statistical and spatial data, were the first to provide unsupervised region-based segmentation. Recent unsupervised 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].

In the context of autonomous mobile robotic exploration in cluttered environments, the value associated with each cell of an occupancy map corresponds to the probability of this cell being occupied, resulting in clustered distributions of textures. Therefore, region-based segmentation appears to be well suited to ensure obstacle location and identification of safe areas for the robot to navigate. As well, object identification can eventually be achieved by shape recognition to provide controlled interaction with the environment. Considering that the workspace configuration is initially unknown and get scanned by a laser range finder only along specific directions, the resulting map of explored space is characterized by a series of edges corresponding to the rays emitted by the active range sensor. Under such conditions, a segmentation approach that combines contrast and texture properties to identify regions of uniform density reveals to be an appropriate strategy for differentiating between segments present in a probabilistic map.

Ojala *et al.* [12, 13, 14] proposed such a segmentation technique based on "Local Binary Pattern" and "Contrast" (*LBP/C*) to subdivide images with sharp patterns. But unlike the images that they considered, in probabilistic maps transitions between free and occupied spaces do not define clear boundaries and are spread out according to the uncertainty level introduced by the sensor model. Refinement to the original *LBP/C* segmentation mechanism has been proposed in [15] to handle smooth transitions in complex images while achieving accurate contours definition. Here, the work is extended and an evaluation is conducted on the application of segmented probabilistic occupancy maps for path planning and collision avoidance with a mobile robot. In order for the planning to be successful, the probabilistic space must first be segmented into areas of a relative size with uniform occupancy. The application of probabilistic maps for path planning extensively depends on the success of the segmentation step. This aspect has not been widely investigated in the literature while taking into account realistic sensing mechanisms that do not provide an absolute knowledge of the state of the space around the robot.

The following sections summarize the extended probabilistic maps segmentation technique based on the double distribution of "Local Binary Pattern" and "Contrast" (*LBP/C*) used to describe textures. Next the impact of the proposed segmentation technique on safe trajectory planning is investigated and experimental results are presented to demonstrate the validity of the approach.

II. Segmentation Algorithm

In a similar way to the approach introduced by Ojala *et al.* [12], the proposed segmentation algorithm is 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 original algorithm. However, the proposed approach introduces major changes into the second and third stages to adapt and optimize the original algorithm to handle probabilistic images, while significantly reducing 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 that only approximate the various regions present in the image. Therefore, a final 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 new uniformity test is introduced to determine if a given region of size [α x α] contains heterogeneous textures and therefore must be subsequently subdivided into four sub-regions of equal size. Initially the four sub-regions of size [$\alpha/2$ x $\alpha/2$] are identified and a logarithmic likelihood ratio is computed between each of the six possible pairs. The largest and the smallest G-statistic values, eq. (1), denoted respectively by $G_{\max}^{\alpha/2}$ and $G_{\min}^{\alpha/2}$, are identified among those pairs.

$$\begin{aligned} G^{\alpha/2} = {} & 2\left[\sum_{s,m}\sum_{i=1}^{n} f_i \times \log(f_i)\right] - 2\left[\sum_{s,m}\left(\sum_{i=1}^{n} f_i\right)\times\log\left(\sum_{i=1}^{n} f_i\right)\right] \\ & -2\left[\sum_{i=1}^{n}\left(\sum_{s,m} f_i\right)\times\log\left(\sum_{s,m} f_i\right)\right] + 2\left[\left(\sum_{s,m}\sum_{i=1}^{n} f_i\right)\times\log\left(\sum_{s,m}\sum_{i=1}^{n} f_i\right)\right] \end{aligned} \tag{1}$$

In eq. (1), 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 them [15].

The parent block is considered non-uniform and thus subdivided if the ratio between $G_{\max}^{\alpha/2}$ and $G_{\min}^{\alpha/2}$ is higher than a certain threshold designated by *X*:

$$R^{\alpha} = \frac{G_{\max}^{\alpha/2}}{G_{\min}^{\alpha/2}} > X, \alpha \in \{64, 32, 16\} \tag{2}$$

Setting of the threshold value is guided by the fact that supplementary subdivisions that segment regions without strong distinctive features can easily be corrected in the second phase. On the opposite, segments missed in the first phase cannot be reintroduced afterwards. An over-segmentation is therefore privileged in this early phase. In the case of 2D probabilistic maps, a choice of *X*=1.2 performs well, since 20% of variation between the largest and the smallest G-statistic values corresponds to a perceptible deviation in the region's texture.

The hierarchical division phase starts by subdividing the entire probabilistic image into blocks of [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. As shown in Fig. 1, if the test result is positive for a given block, four sub-blocks of size [32x32] each are obtained. In this case, each of these blocks is submitted to the uniformity test described above which decides if a second level of subdivision is necessary. A positive level-two subdivision result is represented for the top right [32x32] block in Fig. 1.

The subdivision process continues iteratively until a stopping condition is met. The minimum size that a sub-region size can reach is 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 experimentation with probabilistic maps of a higher complexity demonstrated that a third level of subdivision, leading to a block size of [8x8], is necessary. The values of α in eq. (2) correspond to the possible sizes of the regions which undergo the uniformity test. Fig. 1 illustrates the recursive subdivision process in which the upper-right sub-blocks have been obtained after three levels of subdivisions. Despite the computational overhead that is added by this supplementary step, the refinement phase is relieved from a costly reclassification, and more accurate segmentation results are achieved.

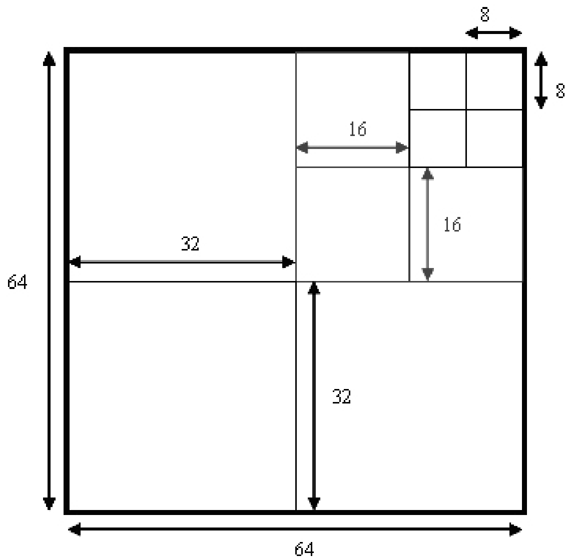


Fig. 1. Representation of the subdivision scheme.

B. Segments Creation

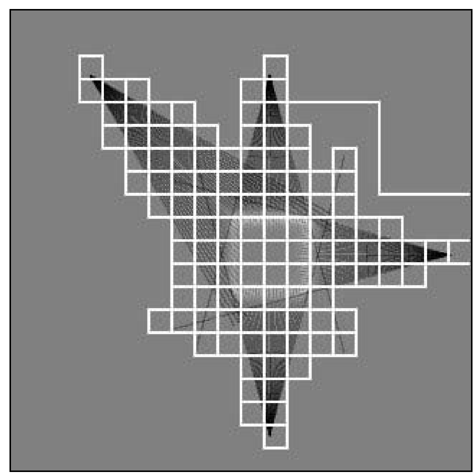
This phase merges similar neighboring regions until a convergence criterion is met. Fusion between adjacent blocks is performed when an average occupancy probability, *OP*, for each block is in the same range. This parameter represents the average pixels intensity level, *I*, in a region R_i of size [*N*x*M*], and is determined as follows:

$$OP_i = \frac{1}{M \cdot N} \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} I\left(r_{k,l}\right) \left| r_{k,l} \in R_i \right. \qquad (3)$$

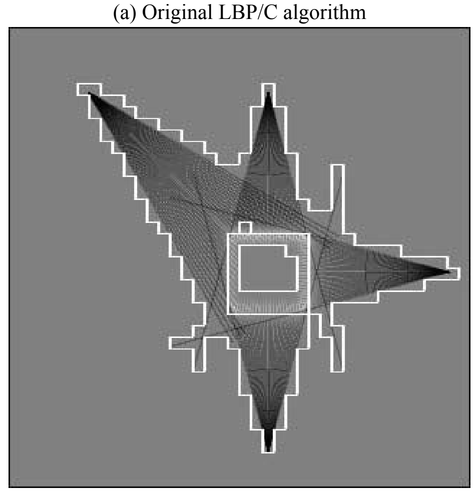
The choice of the *OP* parameter, used to evaluate texture similarity between adjacent regions, is related to the structure of the probabilistic occupancy grid in which pixel intensity values correspond to the probability of space occupancy. After normalizing the pixels' values in the range [0;1], if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

For the purpose of safe robot navigation, the probabilistic map first needs to be segmented into regions characterized by deterministic states, *S*, that is $S(R_i) \in$ *{free, unknown, occupied}* upon which navigation decisions can be performed. These states 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 readily merged together and are classified as a single segment of free shape 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 distinct areas that will eventually be connected by the path planner.

One of the major problems encountered with the original algorithm proposed in [12] comes from the fact that it is incapable of correctly merging segments that correspond to known space, either free of occupied. Thereafter, Ojala *et al.*'s algorithm cannot identify the occupied and free spaces as unique segments. In addition, this algorithm does not provide any information about the occupancy state of the segmented regions. For these reasons, numerous applications, such as path planning for autonomous mobile robots cannot rely on the original *LBP/C* algorithm [12]. Fig. 2 provides a comparison between the segmentation results obtained on the same probabilistic map with the algorithm proposed in [12], and with the enhanced approach introduced in [15]. This shows that the original *LBP/C* algorithm fails at properly merging adjacent uniform regions into single segments while the improved segmentation approach successfully groups free and occupied regions of space in distinct but unified regions that are optimal for robot navigation.



(a) Original LBP/C algorithm



(b) Proposed algorithm

Fig. 2. Comparison of segmentation results obtained after the second phase.

C. Refinement

Finally, segmentation results are refined by reclassifying the pixels located on the edges between two adjacent regions. 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. As a consequence, the space whose occupancy is known always juts out into the unknown one, which represents potentially hazardous situations for safe robot navigation.

A process of compaction must be applied to the free and occupied segments in order to better delimit them and to expand unknown ones. At the implementation level, this process consists of scanning the probabilistic image along each of the four possible horizontal and vertical directions: 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 that have a value of 0.5 are reclassified as belonging to the unknown region, until a pixel with a different value 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 in probabilistic maps given that sensor's uncertainty is taken into account, the compaction process is revisited. Boundaries between free/occupied (occupied/free) spaces are scanned as for the compaction process described before, from the four possible sides, but in this case if each pixel on the boundary has an occupancy probability equal or below (equal or higher than) 0.5, three successive pixels are considered along the scanning direction. Three cases are then possible. First, if the three pixels have a value of 0.5, no reclassification is done; this case ensures that no holes are created in the segments due to the fact that the rays emitted by the range sensor do not cover the entire space and are often separated by unknown cells due to the angular resolution of the sensor. Second, if at least one of the pixels has an occupancy probability strictly less (higher) than 0.5, the pixels, up to the one under observation, are reclassified as being free (occupied). The third case corresponds to the situation in which no classification occurs due to the fact that an occupied (free) cell is encountered.

III. PATH PLANNING APPLICATION

In order to evaluate the potential of the enhanced LBP/C segmentation technique as a preliminary processing stage for path planning with probabilistic occupancy maps, a standard *A** path planning algorithm [16] has been implemented and tested with several occupancy maps of various complexity. The well-known *A** algorithm guides a mobile robot toward a destination cell in the map by successive minimization of the remaining distance between the goal and the current location while avoiding prohibited areas. For testing purposes, safe travel areas have been considered as regions characterized by an average occupancy probability below 0.45. The choice of this value is justified by the fact that only areas with average occupancy probability strictly lower than 0.5 can have been scanned by a laser range sensor without being occluded.

On the other hand, regions characterized by an average occupancy probability around 0.45 can be generated under two circumstances. On one side, such a low certainty level on the empty state of space occurs when the region of interest is located far away from the scanner. Given that the laser beam is scanning following a radial pattern, the unscanned area between two adjacent beams is proportional to the distance to the range sensor. The further away from the sensor, the lower is the density of measurements and therefore the lower is the certainty on the state of the space. On the other hand, successive measurements with highly contradictory information resulting from noise or limited reflection of the laser on specular surfaces can also lead to similar occupancy levels. Considering regions with an occupancy probability lower than 0.45 ensures a sufficient safety margin without significantly reducing the workspace. This threshold however remains dependent on the accuracy and resolution of the range sensor.

IV. EXPERIMENTAL RESULTS

Enhanced *LBP/C* segmentation and *A** path planning have been applied in combination on various probabilistic maps representing cluttered bidimensional workspaces. Results are presented here on two probabilistic maps, each of size [320 x 320]. These maps have been generated using a mobile laser range finder simulator for 2D surface mapping that was developed in previous work [17]. Occupied space shape as well as the number and positions of the range sensor's points of view differ between maps. In Fig. 3a and 4a, white pixels represent the surface of objects, dark pixels correspond to free space, and intermediate grayscale pixels map unexplored areas. The first map (Fig. 3a) contains an object resembling an electrical plug, while the objects used in the following image (Fig. 4a) have a circular and a rectangular shape. Five range sensor scans are taken with a Gaussian error (σ^2=16) on the range measurements and merged to build the probabilistic maps shown in Fig. 3a, while six scans are used in Fig. 4a. The step angle between two adjacent sensor's rays which defines the angular resolution is fixed to 0.5 degree in all maps to create non-uniform textures in explored spaces.

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 is [64x64], and three subdivision levels are conducted, leading to a minimum subdivision level of [8x8]. Fig. 3b and 4b present the results of the hierarchical division phase of the algorithm, while Fig. 3c and 4c show the segmented maps after the segments creation phase.

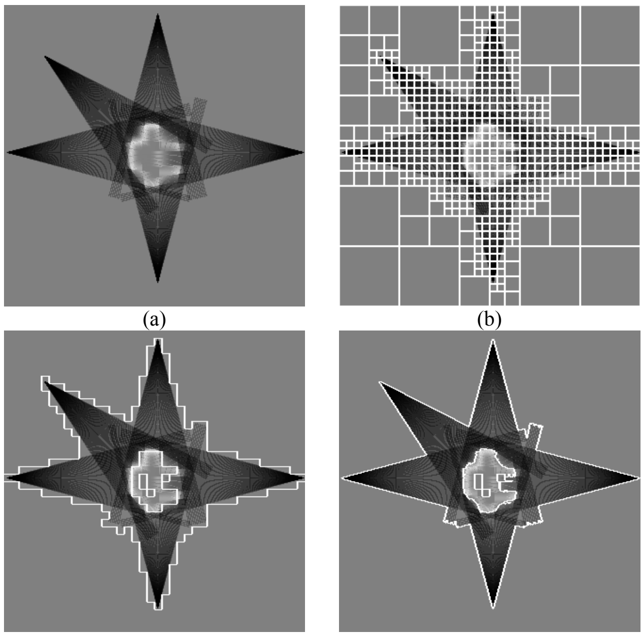


Fig. 3. Probabilistic map segmentation on a complex object.

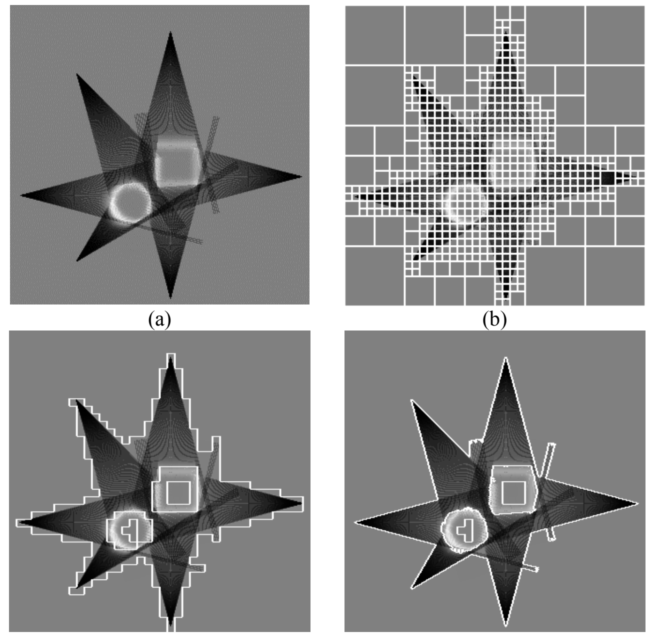


Fig. 4. Probabilistic map segmentation with extra viewpoints.

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 in Fig. 3. 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 that of Fig. 3. The rough localization of contours between free and unknown space is also obvious in both cases.

Segmentation results obtained after the refinement phase are shown in Fig. 3d and 4d respectively for the two probabilistic maps. 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].

Path planning results with the A^* algorithm are presented in Fig. 5 and 6 for the two probabilistic maps shown respectively in Fig. 3a and 4a. The parameters of the path planner are those described in section III. In Fig. 6 and 7, the safe travel space characterized by a low occupancy probability is shown in black, while the occupied and unknown spaces considered as unsafe are represented in intermediate grayscale intensity. The fact that no distinction is made at this level between objects and the unknown space is justified by the need to plan the trajectory only in areas where no object can be encountered. The path followed by the robot is shown in white. During his movement, the mobile robot chooses as the next step destination, the free cell that minimizes the distance with its final destination.

For this reason when the robot meets an unsafe travel area on his trajectory, it runs along its borders while minimizing the distance criterion. Even though the trajectories are not optimal in nature due to the simplicity of the path planning algorithm that is used, these experimental results demonstrate that the enhanced *LBP/C* segmentation algorithm can provide major improvement on the traversability of space, the safety of the robot and the smoothness of the resulting path, independently from the sophistication of the planning algorithm, when probabilistic occupancy maps are used. Safe navigation areas being readily unified by the segmentation phase reduces the search effort for a collision-free path.

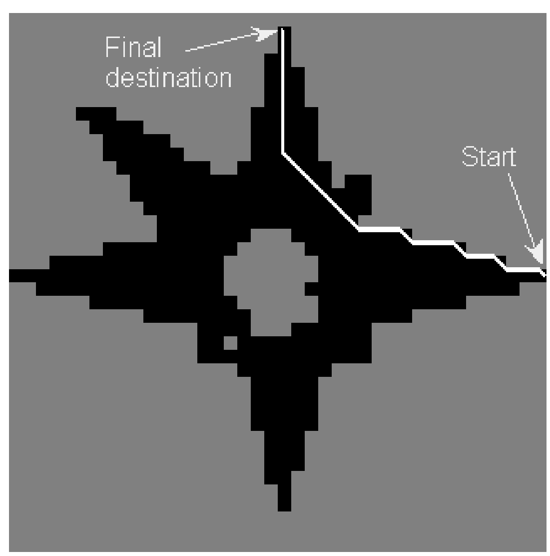


Fig. 5. Trajectory restricted to the safe travel space.

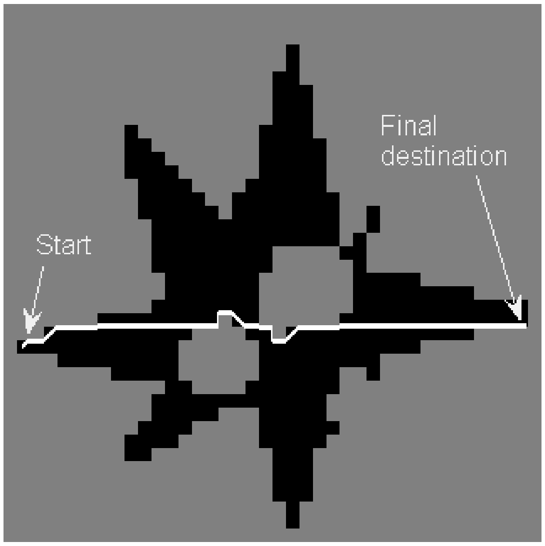


Fig. 6. Path planning involving objects avoidance.

This research work demonstrates that the enhanced segmentation 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. The proposed algorithm is also computationally efficient. The complete segmentation and path planning processes for the environments shown in Fig. 6 and 7 took between 35 and 40 seconds when running on a Matlab 7.0 platform with a 1.8 GHz Pentium M processor. By translating the code to C, computational time was reduced by a factor of more than 10 leading to an execution time between 2 and 4 seconds for the complete task. When 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.

V. Conclusion

An enhanced version of the local binary pattern and constrast (LBP/C) segmentation algorithm has been proposed and adapted to efficiently process bidimensional probabilistic occupancy maps represented as textured images. Experimental results on environment maps of various complexity demonstrated the accuracy and the computational efficiency of the proposed approach over the original technique found in the literature. An application to safe mobile robot navigation in cluttered environments strictly guided by segmented 2D occupancy maps acquired with realistic range sensors submitted to limited spatial resolution proved the relevance of the approach for collision-free robot path planning and interaction control with the environment. On-going research aims at extending the proposed technique for segmentation of 3D probabilistic occupancy maps to also allow guidance of manipulator robots.

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