# Real time EM segmentation of occupancy grid for robots navigation

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## Abstract

Present work deals with the generation and maintenance of a local environment representation for an indoor robot to capture the dynamism of office scenarios. The final representation is composed of a set of segments, namely a map, that describes the obstacles sensed in a short temporal window. Segments are derived by clustering the cells of an intermediate 2D grid that accounts for the evidence of occupancy inferred from sonar measurements. Clustering is performed by means of the statistical fast EM algorithm that iteratively updates in real time the segments population. The more relevant feature concerns real time upgrading of the segments map to deal with dynamic objects for local navigation tasks.

## 1 Introduction

Map building is one of the most appreciated abilities in a robot that has to perform autonomous navigation. While maps have been intensively introduced by a human the progress towards autonomy in artificial systems points ever more to the self building of world models to deal with unknown environments and dynamic objects.

Most work on environment representation for robots navigation deals separately with global maps that permit long term path-planning and almost instantaneous representation of obstacles to react to unpredictable events [García-Alegre *et al.*, 1993],[Simmons *et al.*, 1997]. In order to capture the dynamism inherent to many ambiences an instantaneously updated short term representation is proposed for local navigation tasks. This spatio-temporal description offers a representation more reliable and abstract than those closer to instantaneous sensor readings [Cañas *et al.*,1998], fast enough to capture dynamic obstacles.

Whithin the metric map approaches the occupancy grid paradigm ([Elfes, 1990], [Moravec, 1988]) and the geometrical elements model ([Gasós and Martín, 1996], [Leonard *et al.*, 1992],[Cox and Leonard, 1994]) arise as the most successful methods of accounting for uncertainty in sensors readings. Present work tries to integrate the more relevant aspects of both methods by a continous updating of an occupancy grid as new sonar measurements are obtained and by clustering the grid cells with high occupancy values into geometric elements, namely segments. The clustering is performed in real time by means of the EM algorithm that iteratively finds the segments map that more closely fits the occupancy cells in the updated grid.

## 2 Sonar model and short term memory

Around the grid paradigm several approaches have been used by the robotics community to deal with sensor uncertainty: probability [Thrun *et al.*, 1998], evidence theory [Pagac *et al.*, 1996], fuzzy sets [Oriolo *et al.*, 1998], etc. The proposed model is based upon an histogramic approach [Borenstein and Koren, 1991], wherein sonar and encoder readings periodically provide information on obstacles and on the robot location. Each sonar measurement is translated into a set of occupancy and empty points, following the model in figure 1, where circles represent empty points randomly located in the angular cone and crosses hold for detected obstacle position.

According with [Pagac *et al.*, 1996] and the sonar receiver operation the obstacle evidence is distributed randomly in the whole arc. Despite there is more ultrasonic energy in the central area than in lateral ones, there is no way to discriminate where there is more probability for the obstacle to be in, because all the sectors inside the arc can surpass the energy threshold and then activate the sonar echo detection.

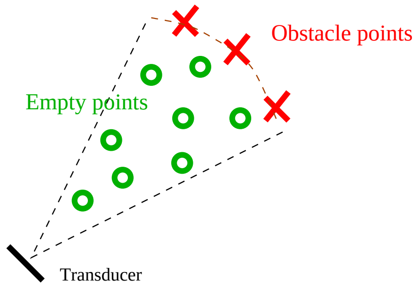


Figure 1: Ultrasonic cone, obstacle and empty points.

Figure 2: Short term memory of obstacle points.

Those random obstacle and free_space points sample all the information contained in the sonar reading. Points are stored in a FIFO *short term memory*; the larger the size the higher the persistence of the perceived stimuli in the robot's memory.

A filter is used to discard too-far sonar measurements and only sonar readings below an *admission distance* are incorporated into the memory, because long distance measurements are usually generated from multiple reflections instead of coming from real objects.

The 2D point coordinates (x,y) are expressed in the same reference system as the odometric readings, with the origin of the reference system located at the initial robot position. Dead reckoning errors with respect to an absolute reference system are irrelevant in this work because the obstacles representation is always relative to the current position of the robot, that is, a robot-centered approach [Elfes, 1990]. All sonar measurements as well as the robot position are affected by the same absolute error, so there is no relative shift among them as far as the memory is not too large.

## 3 Local occupancy grid

Sonar readings are uncertain due mainly to their poor angular resolution and to errors related to specular reflections [Gasós and Martín, 1996]. A short term memory is proposed to store all the occupancy evidences recently obtained and a *small grid around the robot position* is used to represent the state of its surroundings. A decision function calculates the occupancy state of each cell according to the evidences stored in the memory. That function integrates evidences coming either from several sonar sensors, from different robot locations and from different instants. It can also consider the number of empty points laying in that area, the number of obstacle points, the distance they where collected from, whether they are recent or not, etc.

The implemented function is displayed in figure 3 where the occupancy state of a spatial cell depends on

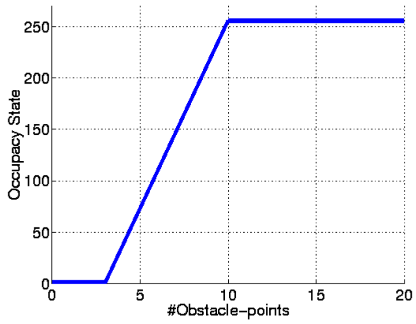


Figure 3: Occupancy function

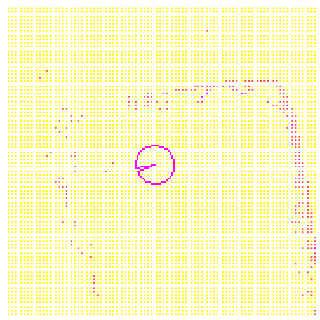

Figure 4: Occupancy grid updated over the points memory

the number of obstacle points within its limits. That state summarizes the belief in the occupancy of that area, ranging gradually from totally empty to fully occupied. Several obstacle points are needed to reach the lowest level of occupancy, thus filtering isolated wrong measurements. On the other hand there is a saturation level that equalizes the belief on occupancy from a selected threshold of obstacle points. Therefore repeated readings are also filtered if they don't add more information to the occupancy state.

Each time a new sonar reading is collected the state of the affected cells in the grid is recalculated using the occupancy function. With this mechanism the grid incorporates new obstacles very fast. Nevertheless it takes more time to forget obstacles that have disappeared as the obstacle points corresponding to past positions persist in the memory for a short while.

The short term memory is always required because the occupancy grid is a moving structure. It has a bounded scope, and it is always centered at the robot location, representing the occupancy state of its local surroundings. The grid changes its location as the robot moves, recalculating the occupancy value of the cells from the data stored in the short term memory.

## 4 EM segmentation

To get a more compact representation the occuppied cells of the grid are clustered together in segments. The iterative estimation technique EM (Expectation-Maximization) is used to periodically adjust a segment population to the content of the moving grid. This algorithm has been successfully used in computer vision to segmentate visual images [López-de-Teruel and Ruiz, 1998], and also in map generation as a fast optimization algorithm [Thrun *et al.*, 1998].

The EM algorithm is used in current work to estimate the occupancy probability density function around the robot location. This density function is estimated as a finite combination of $k$ classes where each class is a bidimensional gaussian $G_k$ weighted by a factor called class probabability $P_k$. Each class holds for an occupancy segment representing an obstacle, its mean $\{\mu_x, \mu_y\}$ determines its position, and the covariance matrix $\{\sigma^2_{xx}, \sigma^2_{xy}, \sigma^2_{yy}\}$ defines its size and orientation. A point $C_i$ near the robot has the estimated occupancy probability $P_{occupacy}(C_i)$, where

$$P_{occupacy}(C_i) = \sum_{k,N} P_k \; p(C_i/G_k) \tag{1}$$

The grid cells are considered now samples of the current occupancy probability density function. Each cell $C_i$ weights as much as its occupancy state and the total weight of all the occupied cells is named $I$. The probability of a sample in a cell $C_i$ to be generated by segment $G_k$ is assumed to be the value of that bidimensional gaussian at that location $C_i = \{x, y\}$.

$$p(C_i/G_k) = \frac{1}{2\pi}\frac{1}{\sqrt{\sigma^2_{xx,k}\sigma^2_{yy,k}(1-\sigma^2_{xy,k})}} \; e^{\frac{1}{2(1-\sigma_{xy,k})}\left[\left(\frac{x-\mu_{x,k}}{\sigma_{xx}}\right)^2+\left(\frac{y-\mu_{y,k}}{\sigma_{yy}}\right)^2\right]} \; e^{\frac{-\sigma_{xy,k}}{(1-\sigma_{xy,k})}\left[\left(\frac{x-\mu_{x,k}}{\sigma_{xx}}\right)\left(\frac{y-\mu_{y,k}}{\sigma_{yy}}\right)\right]} \tag{2}$$

EM finds the gaussian parameters and class probabilities that best fit the probability density estimation to the sample contained in the occupancy grid. While adjusting the estimation the algorithm calculates the right position, size and orientation of all the segments.

The algorithm starts with a pool of random gaussians that are iteratively refined in a sequence of Expectation and Maximization steps. With an static image the steps would be iterated until the algorithm converges and the parameters don't change with new iterations. In present approach a dynamic sonar image of the environment is used instead of an static one. EM iterations are continuously run to adapt the segment population to the grid contents and to keep the gaussians set updated to new sonar readings. The EM speed profiling the gaussians must be faster than the speed of moving obstacles in the environment.

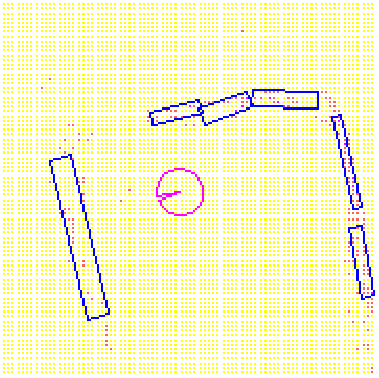

Figure 5: Occupancy segments obtained on the moving grid

The Expectation step[1] calculates the probability of the cells given the current gaussians set and it uses the Bayes theorem to estimate the probability of the gaussians given the current cells. Intuitively this number quantifies the proximity of the cell to the gaussian, the larger $p^t(G_k/C_i)$ the closer the cell.

$$\forall k \in K, \forall i \in I$$

$$p^t(G_k/C_i) = \frac{P_k^{t-1}\, p(C_i/G_k^{t-1})}{\sum_{k=1}^{K} P_k^{t-1}\, p(C_i/G_k^{t-1})} \tag{3}$$

In the Maximization step[1] the parameters of every gaussian are estimated again using the computations of the prior Expectation step. Intuitively the position, size an orientation of every segment is reestimated among the points closer to it, so that the gaussian fits the points that it covers.

$$P_k^t = \frac{\sum_{i=1}^{I} p^t(G_k/C_i)}{I} \tag{4}$$

$$\mu_{x,k}^t = \frac{\sum_{i=1}^{I} \frac{p^t(G_k/C_i)}{P_k^t} x_i}{I} \tag{5}$$

$$\mu_{y,k}^t = \frac{\sum_{i=1}^{I} \frac{p^t(G_k/C_i)}{P_k^t} y_i}{I} \tag{6}$$

$$\left[\sigma^2_{xx,k}\right]^t = \frac{\sum_{i=1}^{I} \frac{p^t(G_k/C_i)}{P_k^t} (x_i - \mu_{x,k}^{t-1})^2}{I} \tag{7}$$

$$\left[\sigma^2_{yy,k}\right]^t = \frac{\sum_{i=1}^{I} \frac{p^t(G_k/C_i)}{P_k^t} (y_i - \mu_{y,k}^{t-1})^2}{I} \tag{8}$$

$$\left[\sigma^2_{xy,k}\right]^t = \frac{\sum_{i=1}^{I} \frac{p^t(G_k/C_i)}{P_k^t} (x_i - \mu_{x,k}^{t-1})(y_i - \mu_{y,k}^{t-1})}{I} \tag{9}$$

Two enhancements have been added to this standard EM algorithm to improve its performance on ultrasonic images: first, a *belongs_to* function has been defined to

[1]The subscripts mean number of segment and the exponents the number of iteration

assign each cell to the closer gaussian, if any (10). The cells far from all the segments remain unassigned. With this relationship the class probability is calculated as the fraction of occuppied cells that belongs to that class (11). This is a better estimator for $P_k^t$ than the standard EM one and avoids some degenerated behavior.

$$C_i \in G_j \Leftrightarrow \begin{cases} p(C_i/G_j) = \max_{\forall k \in K} \quad p(C_i/G_k) \\ p(C_i/G_j) > distance\_threshold \end{cases} \quad (10)$$

$$P_k^t = \frac{\sum_{i=1}^{I} belongs\_to(C_i, G_j)}{I} \quad (11)$$

Second, class probability is considered as a quality measurement. Gaussians that don't cover any occupied cells have null quality, and good segments should cover some of them, the more the better. If the quality indicator falls below a minimum threshold that segment is discarded as a representative of an environment obstacle and a new random segment is introduced into the EM tuning process. In order to accept a segment as a valid obstacle descriptor it has to surpass an acceptable quality threshold.

## 5 Experimental results.

Several experiments have been performed to test this perceptual approach on a commercial robot RWI B21. This mobile platform is equipped with a belt of 24 sonar sensors which delivers three ultrasonic images per second and a dead reckoning system that delivers five position measurements per second. In these experiments a reactive controller commands the robot to follow walls, at a maximum drive speed of 0.1m/sec and at a maximum steer speed of fifteeen degrees/sec. All the processing is done in the Intel 486-66Mhz onboard computer but the spatial representations are displayed on real time off board, through a radio link.

Tests were made to fine tune some of the parameters of the map building process. In such a way, only two obstacle points are generated inside the arc per each sonar measurement and the memory is fixed to 8000 points size, resulting in one minute persistence of sonar data in memory. The admission distance is configured to 0.7 meters, reaching a good trade off between filtering wrong sonar readings and detecting obstacles soon enough to avoid them at the current drive speed. The grid size is set at 2x2 meters around the robot, discretized in cells of 5x5 centimeters with only three levels of occupancy.

The number of segments in the pool is another trade off between expressive power and speed for capturing new obstacles on one hand versus computational cost and then slow segment update on the other. Twelve gaussians are used in the experiments to cluster the occupancy grid without slowing too much the clustering process that runs at two EM iterations per second.

The segment set inherits the scope of the grid and adds a short delay in representing the environment, just the time needed to adapt the segments to a new situation. Occupancy segments updated over the dynamic

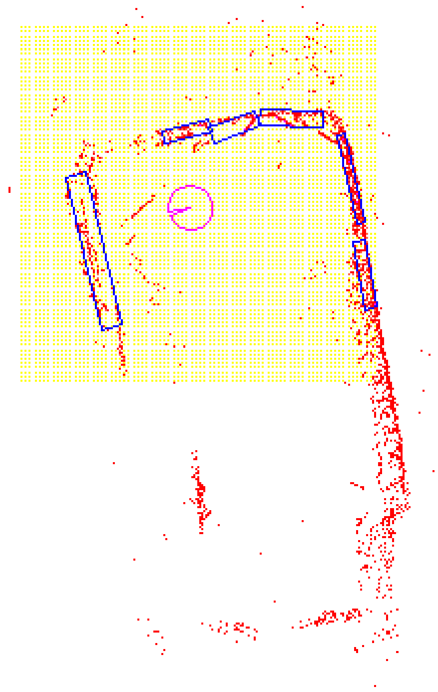

Figure 6: Occupancy segments updated over the dynamic grid, capturing the wall

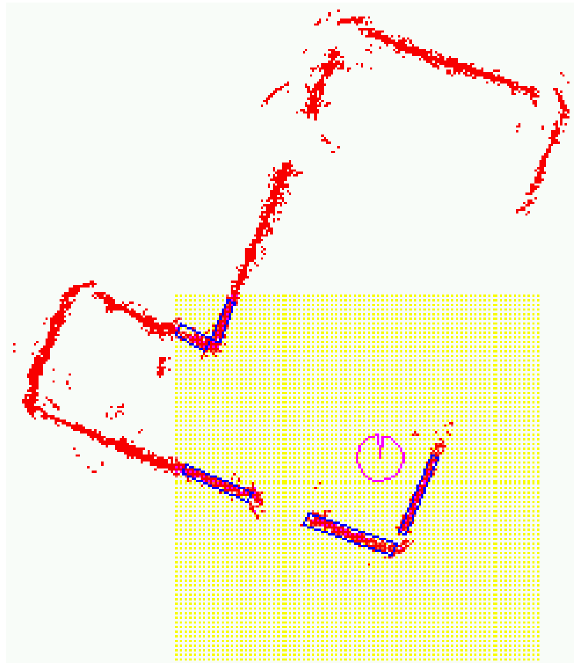

Figure 7: Occupancy segments capturing the corner and the door hole

grid are shown in figure 6 and figure 7. Main walls are well represented by aligned segments as well as a hole corresponding to a 60 cm width door, low left corner in figure 7. Segment width corresponds to the degree of uncertainty in the obstacle edges detection, due to the different sonar and dead-reckoning errors.

## 6 Comments and conclusions

The environment representation is structured upon three main concepts: point, cell and segment. The map segments is periodically updated in order to reflect quick changes in the robot surroundings, capturing the dynamism of the environment in an alternative approach to Kalman filtering [Cox and Leonard, 1994].

This spatio-temporal representation integrates sonar readings coming from either different sensors and robot positions providing reliability and robustness against sonar failures. Reliability could be reinforced considering also the empty-points when deciding the occupancy degree of the grid cells. The presented approach also allows for a global exploitation of all gathered sonar readings permitting the appearance in the map of stimuli not fully contained in every single sensor measurement, like segments, walls, holes, etc.

The high computational efficiency of the EM algorithm enables the construction in real time of a continously updated segments representation. Such local maps will be further exploited by other processes dealing with active sensing, local navigation or longer term planning strategies.

Current implementation is relatively slow in forgetting objects that disappear. To overcome this drawback and to fully capture the dinamism of the environment new occupancy functions could be developed to take into account empty-points and the admission time of the sonar readings to better decide on the occupancy state of the grid cells.

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