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3D ROBOTIC MAPPING WITH PROBABILISTIC OCCUPANCY GRIDS

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ABSTRACT

We propose a new approach to 3D environment mapping from a mobile robot, using visual information provided by alow-cost stereo vision system. Depth information recovered from disparity maps serves as input for our method that uses probabilistic modelling to determine if a region is occupied or freein an occupancy grid approach. There is no similar approach in the literature, based on statistical modellingof the errors from stereo measurements and robot's motion, so this is the main contribution of this work. The resulting map canbe directly used in tasks like obstacle avoidance, navigation, localization, exploration and path planning,enabling a mobile robot to perform autonomous navigation in its environment. Real experiments done with a Pioneer 3-AT mobile robot equipped with a Minoru stereowebcam show the efficiency of our mapping approach.

KEYWORDS: *Occupancy Grid, Stereo Vision, 3D Mapping.*

I. INTRODUCTION

The mapping of environments is considered so far anessential task in autonomous robotics applications [1] [2]. Byhaving knowledge about object positions and free pathwaysinside the environments a mobile robot can interact with them in a moreflexible way. The robot can rely on the maps for safelynavigating in the environments, avoiding obstacles and dealingwith unexpected situations. Without a map, the detection ofobject positions would be more difficult and, consequently,the path planning strategy more complex.

To do this the robots needs to be equipped with sensors, which enable it to collect information about its surround. Several types of sensors can be used for carrying out amapping task. Most commons are sonars, lasers and cameras.Sonars are an attractive alternative because of the associatedlow cost. In a previous work [3], we used a robot equipped with sonars to construct anoccupancy grid map, which is based on sonars' information.It is known that this type of sensor presents significantinaccuracies in the measurements acquired. Lasers, on theother hand, are highly accurate and provide data that canproduce more detailed maps [4]. However, because its highmonetary cost they are not so attractive.Cameras are sensors that are getting cheaper each day and make possible the acquisition of a large amount of datarobot's surrounding. Besides, the advantages provided bycurrent technological advances as light weight, small size,some embedded processing, and energy economy that makecameras a usual choice for any type of robot. The use ofartificial vision systems allows the implementation of functionalities thatare essential to robotics as: obstacle detection, tracking, and visual servoing. For these reasons, cameras are reaching animportant role among the sensors used for robotics mapping.

Through computer vision algorithms, data coming fromcameras can be mapped into a lot of improved information. From visual data, it is possibleto get depth information, features as, points,lines, corners, texture, and even the geometry of objects andobstacles present in the environment. Furthermore, it is possible to estimatethe motion of the robot relative to its environment, from imagesequences [5].

Based on these claims, we propose a new approach for3D robotic mapping using data provided by a stereo vision system andprobabilistic methods to produce as output an occupancy gridmap of the environment. By using stereo vision, a robot cancollect trustable depth data anywhere,with no matter about what typeof environment and characteristics presentinside it. That is, there are no restrictions of theenvironment to be populated by specific features. In this work, we have used alow coast stereo systemused to acquire visual data.

It is well known that visual data have errors which canaffect the estimation process to determinatethe correctcoordinates of the detected points with respect to a referencefixed in the world [6]. Furthermore, robot motions are inaccurate due to systematic and non-systematic factors [7]. Based onthese assumptions, our mapping algorithm considers using aprobabilistic approach that models the uncertainties inherent to boththe sensory data androbot's motion.Thus, resulting maps are coherent with sensory informationacquired by the robot. Mainly, the robot has a well-knownestablished limit for the error, relying in more trustableinformation for decision making.

In this work, we performed several experiments inorder to validate our approach. First, we verified the betterstereo algorithm to generate a dense disparity map. Then,we confirmed the feasibility of the proposed mapping in areal environment which presents typical scenes of indoor andoutdoor places.

This text is organized as follows. Following Section 2shows the fundamentals about robotic mapping necessary to understandour approach, including the basics of the techniques for probabilisticoccupancy grid construction. Section 3presents the stereo vision problem.Section 4 introduces probabilistic modelling of the visualsensor and its uncertainties. Furthermore, this section presents the algorithm of our method. InSection 4, we validate our method with practical experiments.Section 5 makes a brief discussion about the results an points to the applications that can use the proposed technic. Section 6 gives a final analysis of our approach and waysto get it improved.

II. ROBOTIC MAPPING

Robotics mapping can be defined as the process of acquisitionor construction of a spatial model of an environment usingdata provided by robotic sensors and devices. Several waysfor representing maps are proposed in the literature. A classificationlargely accepted is the one proposed by Thrun [1],which classify them in two categories: metric and topologic.A metric representation stores the geometric properties ofthe environment, while the topologic representation stores theconnections (and their properties) between environment places.

Between the metric ones, occupancy grid model proposed by Elfes [8] is one of the most used. The occupancy gridapproach is easy to construct and it can be as accurate asnecessary by the task. This model represents the environmentusing a regular grid composed by cells, implemented byan array, in which the cells store the occupancy probability for a place of the environment. Data coming from sensors are interpreted to give an estimative of the occupancy probability of a cell. It is possible to update the cell values every time ameasure is performed through a Bayesian approach.

Note thata subset of the whole representation is updated each time.This resulting probabilistic model can be used directly as amap of the environment in navigation tasks as path planning,obstacle avoidance, and pose estimation. Figure 1 illustrates therepresentation of a depth sensor measure in a 2D occupancygrid

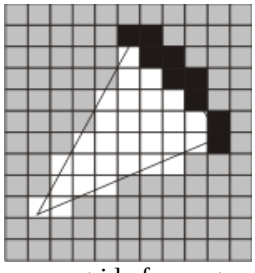


Figure 1. Occupancy grid of a range sensor reading.

Mapping using an occupancy grid representation is implemented by determining the occupancy probability of each cell.A relaxed restriction is to assume that the cells occupancyprobabilities are decoupled, that is, the probability that acell is occupied does not affect the estimation of probabilityoccupancy values for its neighbouring cells. Besides this isnot an ideal assumption specifically in the case of cellsrepresenting the same object, it makes easier to implementthe mapping algorithm without a substantial increasing in themeasured error. The probability of occupation of a map **M**can be factored into the product of the occupancy probabilityof each cell individually, according to Equation 1.

$$P(\mathbf{M}|\mathbf{s}_{1:t}, \mathbf{z}_{1:t}) = \prod_n p(m_n|\mathbf{s}_{1:t}, \mathbf{z}_{1:t}) \quad (1)$$

The construction of the map **M** depends of the historicof robot localizations $\mathbf{s}_{1:t}$and of the sensors readings $\mathbf{z}_{1:t}$performed in each localization. Updating the map is a processof repeating these readings, which can be performed fromother locations with other orientations. In practice, only cellscurrently inside the field of view of the sensor areupdated. The occupancy value of a cell m_n is calculated by Equation 2.

$$p(m_n|\mathbf{s}_{1:t}, \mathbf{z}_{1:t}) = 1 + \frac{1}{1+e^{l_{t,n}}} \quad (2)$$

Where,

$$l_{t,n} = l_{t-1,n} + log\frac{p(m_n|\mathbf{s}_t,\mathbf{z}_t)}{1-p(m_n|\mathbf{s}_t,\mathbf{z}_t)} + log\frac{1-p(m_n)}{p(m_n)} \quad (3)$$

The term$p(m_n)$ is the value of occupation for cell $m_n$previouslyto any measurement which can be attributed accordingto the obstacles density in the environment. The probability$p(m_n|\mathbf{s}_t, \mathbf{z}_t)$ specifies the occupancy probability of cell $m_n$conditioned to the sensor reading $\mathbf{z}_t$and to the robot position$\mathbf{s}_t$ at the time t. This function is named inverse sensor model.More details of the standard algorithm for occupancy grid canbe found in the work of Thrun[9].

Occupancy grids can also be used for 3D environmentmapping, including information about the height of obstacles.Liu et al [10] justified the use of such approach arguing thatheight information can be used to solve the data associationproblem in robotic mapping because 3D models have moreinformation than 2D models, thus having less ambiguity. Moravec [11] was the first to present results of 3D occupancygrid mapping from a stereo vision system. More recentresults using the same technique can be found in the work of Andert [12], however the author used a more robust modelfor data processing from the sensors. Different works have presented in the last years about 3D occupancy grid [13][14], however these works provide no way to deal with the uncertainties inherent to robot's motion in the map building process. This affects the credibility of the mapping.

III. STEREO VISION

The term stereo vision is generally used in the literature tonominate problems in which it is necessary to calculate realcoordinates of points in a 3D scene from measurements performed from two or more images taken fromdifferent viewpoints. The determination of the 3D structureof a scene using stereo vision is a well-known problem [12]. Formally, a stereo algorithm should solve two problems:the matching (pixel correspondence) and the consequent 3Dgeometry reconstruction.

3.1. Stereo Matching

Matching problem can be defined as the determinationof pairs of pixels, one pixel from each image in each pair,which correspond to the projection of the points detected in the scene. That is, given a pixel x in the firstimage, the matching problem is simply solved by determiningits corresponding pixel x' in the second image. In principle, asearch strategy has to be adopted to find the correspondences.Several solutions are proposed generally using restrictions tofacilitate the matching. The epipolar geometry is one of these,that makes narrower the search space. This process must be executed for all pixels of the

images captured by the stereo system. Once determined the matching, disparity*d* can be calculated as the difference between the coordinatesof the corresponding pixels in each image. Next, depth forall points in the scene can be calculated by using trianglesimilarity. Determination of matching for all pixels is afundamental step. In fact, due to occlusions and image errors,we get not completely dense matching.

Between the several methods used for matching and disparitymap calculation, in this work we performed experimentswith the two suggested as better in the work of Scharstein and colleagues [15]: *block-matching* and*graph-cuts*.Block-matching determines the correspondence for pairs ofpixels with characteristics that are well discernible. Basically,this method gives as result a disparity map in four mainsteps. The first is a pre-filtering of the images to normalizebrightness and texture enhancement. The second step is thesearch for correspondences using the epipolar constraint. Thisstep performs the summation of absolute differences betweenwindows of the same size of both images to find the matching.As the third step, a posterior filtering is performed in orderto eliminate false matching. In the fourth step, the disparitymap is calculated for the trustable pixels. This method isconsidered fast, in fact, its computational complexity dependsonly on the image size.

Graph-cuts algorithm treats the best matching problemas a problem of energy minimization, including two energyterms. The smoothness energy (SE) measures the smoothnessof disparity between neighbouring pixels, which should be assmooth as possible. The second term is data energy (ED)that measures how divergent are corresponding pixels withbasis on assumed disparity. A weighted graph is constructedwith vertices representing the image pixels. The labels (orterminals) are all the possible disparities (or all discretevalues in the interval of disparity variation). The edge weightscorrespond to the energy terms above defined. The graph cutstechnique is used to approximate the optimal solution, thatcomputes corresponding disparity values (each edge of thegraph) to each pixel (vertex of the graph) [16].

3.2. Geometry Reconstruction

Geometry reconstruction is related to the determination ofthe scene 3D structures. The 3D position of a point *P* in spacecan be calculated by knowing the disparity between positions(in image coordinate system) of the corresponding pair ofpixels x and x', and the geometry of the system.The last is specified in two matrices M (external) and M′(internal). The positions of pixels are used in thematching to calculate the disparity map, which is thenused directly in the process.

In order to better understand the stereoreconstruction problem, we consider the system shown inFigure 2. It has two cameras with optical axes perfectly parallelto each other. The baseline$b$ (distance between each projection center) and the focal distance *f* are known. The two cameraimages are in the same plane (coplanar).

In the Figure 2, O′ and O are the projection center of the cameras, f is the focal distance between the projection center and the image plane,(x'_0, y'_0) and (x_0, y_0) are the coordinateof pixels in the center of the images (intersection of opticalaxes and image planes). Point *P* in the world is projectedin pixels (x', y') and (x, y) in the images. Distance $z_c$of thecamera system to the point *P*can be calculated by Equation 4.

$$z_c = \frac{fb}{d} \tag{4}$$

Where b is the baseline and d is the disparity, given by$d = x' - x$. In practical situations,d is limited considering a maximum and minimum distance of the system to the scene empirically defined (calibrated). The others coordinates of the point $P_c = (x_c,\ y_c,\ z_c)$ in relation to the stereo system can be calculated by using Equations 5 and 6.

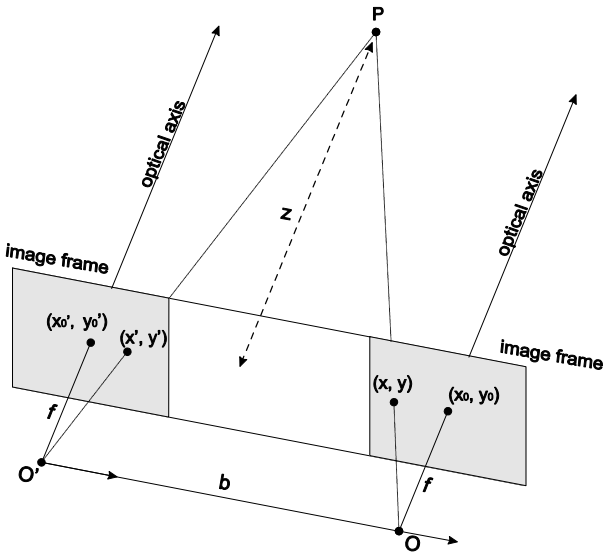


Figure 2. Stereo geometry of a coplanar camera system.

$$x_c = z_c \frac{(x - x_0)}{f} \tag{5}$$

$$y_c = z_c \frac{(y - y_0)}{f} \tag{6}$$

The coordinates of a point in the camera coordinate system$P_c$can be transformed to world frame. To do that, one just hasto know the rotation matrix and translation vector that map thecamera to world frame, and use Equation 7.

$$P_w = R^T P_c + T \tag{7}$$

Parameters *b*, *f*, (x'_0, y'_0) e (x_0, y_0) are determined througha previous calibration of the stereo system. We remark thateven if the system does not follow the restrictions depicted inFigure 2, it is possible to derive a general mathematical modelfor the problem. In this case, it would be more complex torecover the 3D geometry. Besides, in the calibration processit is also possible to diminish or eliminate errors caused bylens distortions and illumination.

IV. PROBABILISTIC MAPPING WITH STEREO VISION

In order to construct the environment representation using occupancygrid, it is necessary to model the used sensor generallynamed the inverse measurement model. We adopt a modellingthat is similar to the one depicted by Andert [12], however we propose to incorporate both the visual data errors whichaffects the estimation process of the correct coordinates ofthe detected points in the world, and the errors inherent torobot's motion in the calculation of the occupancy probability of a cell. With this modification, we get a map that is morecoherent with the sensory data provided by the robot. We canguarantee a limit for the maximum error found in the map.This is extremely important in the treatment of uncertaintiesencountered in the scene to the robot navigation.

The inverse sensor model transforms the data provided by thesensors in the information contained in the map. In our approach, distance measured from a specific point in the environmentindicates the probability that part of the grid is occupied orfree. Distance is calculated directly from disparity. In this way,it is possible to map each point of the space seen by the robotvision system with a valid disparity value into the occupancy values.

In the measurement model, each point of the disparity mapcan act as a distance sensor measured along the ray defined bythe world coordinates of the pixel (in the image plane) and the projection center of

the camera. The point projected on the image planeis given in camera coordinates by$P_c = (x_c,\ y_c,\ z_c)$ and thedistance, l_p, from the camera to P_c is calculated by Equation 8.

$$l_p = \sqrt{x_c^2 + y_c^2 + z_c^2} \tag{8}$$

Each cell$m_n$pertaining to this ray defined by the projection center and point $P_c$in world coordinates must have the occupancy probability according to the Equation 2(section 2) which depends of the inverse measurement modelgiven by Equation 9.

$$p(m_n|\mathbf{s}_t, \mathbf{z}_t) = p_{occ}(l) + \left(\frac{k}{\Delta l_p\sqrt{2\pi}} + 0.5 - p_{occ}(l)\right) e^{-\frac{1}{2}\left(\frac{l-l_p}{\Delta l_p}\right)^2} \tag{9}$$

Where,

$$p_{occ}(l) = \begin{cases} p_{min}, & if\ 0 < l \leq l_p \\ 0.5, & if\ l > l_p \end{cases} \tag{10}$$

This one-dimensional Gaussian model translates noisy sensorydata into information of occupation, considering the uncertainties.The parameter *k* specifies the significance of a singlemeasurement. The constraint $\forall\, l \geq l_{min}: p(m_n|\mathbf{s}_t|\mathbf{z}_t) \in [0:1]$must be fulfilled to ensure that the resulting probabilitiesare valid [15]. The error, Δl_p, in the measured distance can beestimated by Equation 11.

$$\Delta l_p = \Delta z_c \frac{l_p}{z_c} + \varepsilon \tag{11}$$

In this expression we take into account the uncertainty inherent tothe robot motion ε and the uncertainties in the estimation ofthe distance from camera to the obstacle Δz_c. The errors inthe robot motion given by ε is a function modelled in ourprevious work [3]. The uncertainties in the distance Δz_c canbe calculated by the Equation 12.

$$\Delta z_c = \frac{z_c^2}{bf}\Delta d \tag{12}$$

The acquisition and manipulation of disparity images producesan uncertainty Δd in the coordinates of thepixels,named depthresolution. Δd can easily exceed three-tenths of a pixel, whichtranslates to a significant amount of range errors,Δz_c [6].Figure 3 shows a typical inverse sensormodel behaviour with occupancy values. Note that near distancemeasurements results in more significant occupancy value andfar distance measurements low occupancy value.

4.1. Modelling Sensor Uncertainties

According to Xiong and colleague [6] two major errorsources for a real-time stereo system in the context of thenavigation of an autonomous vehicle are: foreshortening errorand misalignment error. These errors can induce significant uncertainties in the estimation of the coordinate z_c, which is animportantdata to estimation of l_p (Equation 8). Note that l_p is important information to the inverse sensor model (Equation 11).

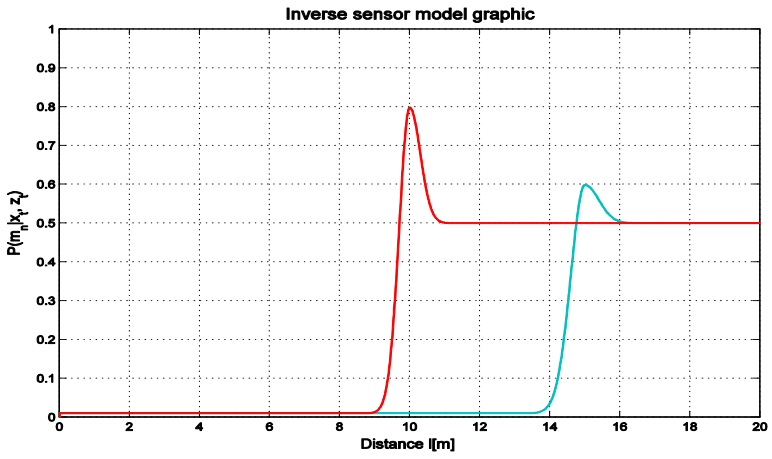


Figure 3. Inverse sensor model simulation values, withl_p $10m$and $l_p = 15m$. In the red curve we have $\Delta z_c = 0.2m$ end the cyan curve $\Delta z_c = 0.3m$.

4.1.1. Foreshortening Error

Results from the fact that the 3D scene is not frontal-parallel. Therefore, for any small patch in the left imageI_l, its corresponding patch in the right image $I_r$is not only translated but also distorted. This error,Δe_f, can be estimated by the Equation 13.

$$\Delta e_f = a.e_f \tag{13}$$

where a is the disparity gradient and e_f is named foreshortening sensitivity. The gradient disparity, a, indicatesif areas of the left and right images can be compared and correlated. Li and Hu [17] show a method to calculatethis variable. Xiong and Matthies [6] explain how to estimate the foreshortening sensitivity, e_f .

4.1.2. Misalignment Error

The misalignment problem can be solved from a stereo calibration step. But in some terrains, like outdoornavigation there are extensive mechanical vibrations, whichcan often perturb camera parameters. The effectsof this error can be modelled by Equation 14.

$$\Delta e_m = m.e_m \tag{14}$$

Where m is the vertical misalignment and $e_m$misalignment sensitivity error. In some investigations [6][18], theauthors suggest values in the interval [0:11; 0:31] to m, even the stereo system has been calibrated. Xiong and Matthies [6] also explain how to compute the misalignment sensitivity error e_m. The total error in the disparityestimation Δd is estimated by the sum of Equations 13 and 14, defined by Equation 15.

$$\Delta d = \Delta e_f + \Delta e_m \tag{15}$$

Δd can easily exceed three-tenths of a pixel, which translates to a significant amount of errors.

4.2. Map Build Algorithm

This subsection explains the way which the 3D mapoccupancy grid map is constructed from depth images. Inthis procedure the estimation of the occupation of each cellwithin the visual field of the camera is given by iteratingover the pixels of the image depth, this approach is basedon line drawing approach [12]. For each depth image pixelis calculated the projection ray from the camera center to the3D coordinate of the point in the worldP_w. The points onthat line will have a value occupancy calculated accordingto the inverse sensor model (Equation 9). This procedure isrepresented by the Algorithm 1.Input data **M**, D_t and $\mathbf{s}_t$ are the grid map valuesestimated on time $t-1$, the depth image or disparity map andthe robot position respectively. The result of this algorithm isthe grid map **M** with updated occupancy values of thecells within the visual field of the camera.

```
Algorithm1: BuilLocalMap
Input: M, D_t, s_t
Output: M
Begin
   For each valid pixel from D_t do
      Calculate the point P_w;
      Calculate the distance l_p;
      Draw a line r from camera center to P_w;
      Calculate l for every cell m_n on the grid intersected by r;
      Calculate the occupancy probability p(m_n|s_t, z_t) of the cell m_n;
      Update the grid map M by p(m_n|s_{1:t}, z_{1:t});
   End
End
```

V. EXPERIMENTS

Initially, we have performed experiments in order to evaluate the better stereo matching algorithm to be used forthe disparity map generation since we use the Minoru 3Dstereo vision system and tested

firstly in indoor scenes. Theimplementation is done using the computer vision OpenCVlibrary [19]. The initial results have shown that graph-cuts algorithmhas achieved better results than block-matching. The disparitymap generated by the graph-cuts is much richer of the weakness of the block-matching to the lack of texture in the indoor scene captured.

Next, experiments to evaluate our main proposal, the use ofstereodisparity as input to the probabilistic approach in theoccupancy grid construction, have been performed. Weuse the Pioneer 3-AT mobile robot equipped with the Minoruwebcam stereo system (Figure 4), and OpenCV library for theimage processing functions. The disparity map was estimatedvia the graph-cuts algorithm.

Figure 4: Pioneer 3-AT robot with Minoru stereo camera.

Welimited the range of the visual sensor with a minimal distance$l_{min} = 0.3m$and a maximal range$l_{max} = 3m$. The foreshorteningerror estimated in this experiment was$\Delta e_f = 0.04$and the misalignment error considered is $\Delta e_m = 0.2m$. Thesevalues have resulted in a total depth resolution (or disparity error) $\Delta d = 0.24$, which can be translated in distance error as showed by Figure 5. If the distance measured from camera to an obstacle is 3m the error associated with depth resolution can produces an error in this measurement of 8cm. This uncertainties needs to be treated by the probabilistic sensor model and the correction of this errors can be achieved by updating the map.

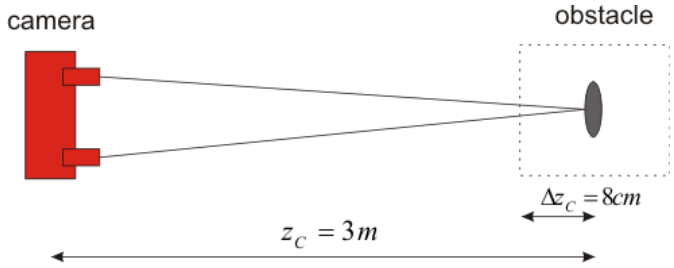
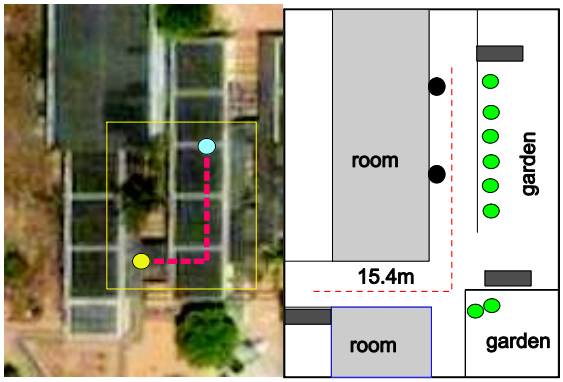


Figure 5: Sensory uncertainties given by disparity process estimation.

In order to perform the main experiment, we have chosen an environment which presents outdoor and indoor scenes, mainly a building area. Figure 6 was taken from Google Mapsand shows the path executed by the robot during mappingwithin the environment. The dashed line represents the followedtrajectory, the blue point illustrates the starting pointand red point represents the end point.



(a) (b)

Figure 6: Path followed by the mobile robot

During the mapping the robot encountered scenes typicalof indoor environments such as hallways, and outdoor scenesfeatures, such as plants. Figure 7 shows images illustrating thesesituations. This generality of applications is an interestingpeculiarity result of joining both approaches used in this work:the occupancy grid mapping and stereo vision technique.

(a) Indoor scene. (b) Outdoor scene.

Figure 7: Distinct scenes encountered during the mapping.

In despite of these differences in scenarios, which results indifferent situations and difficulty in estimating the disparitymap, the proposed algorithm for constructing the 3D mapachieved good results as it can be seen in Figure 8. A 3Doccupancy grid map is shown.In these results only the cells which the occupancy value islarge enough for the robot to believe that in this place thereis an obstacle, are represented. The circled area in yellow represents the 3Dgrid map of the scene typical of indoor and the area circledin red illustrates the map building of the outdoor scene. This result was presented with *rviz* tool, a 3D visualization environment for robots using ROS (*Robotic Operating System*) [20].

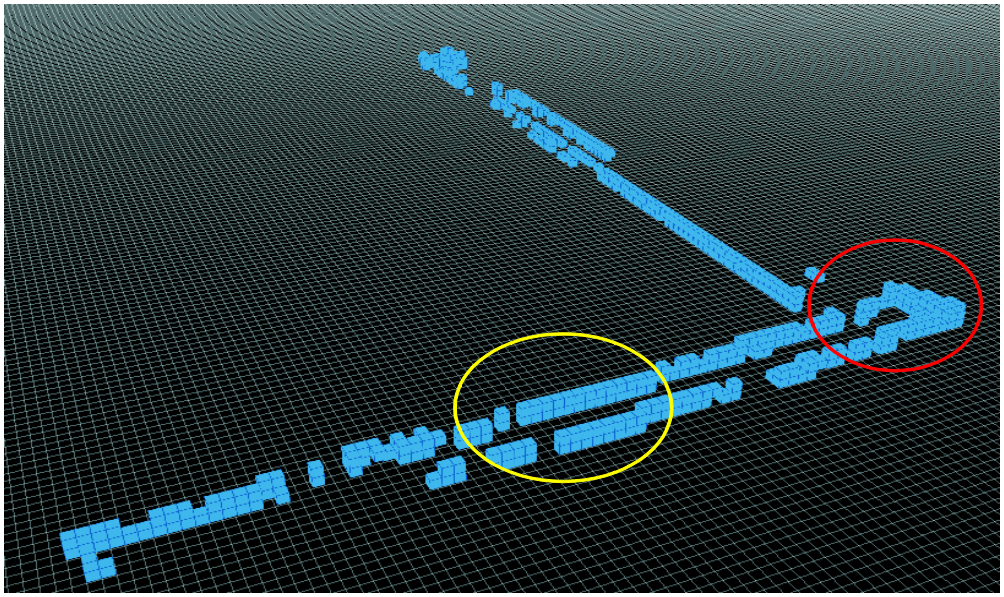


Figure 8: Resultant 3D occupancy grid.

VI. RESULTS AND DISCUSSION

The experiment shows that the proposed mapping can be used directly in tasks like path planning, obstacle avoidance, grid-based localization, etc. Furthermore, this proposedmethod for mapping can help a mobile robot system to reachthe so desired autonomy in the execution of its tasks.Furthermore, with the resultant map the robot can identify traversable areas according to yours motor skills, classifying the obstacles in the map. Higher obstacles can be assigned as non-traversable and lower obstacles can be classifies as traversable point.

More complex environments require a more robust localization technic to provide the exact position of the robot. This can be achieved with *Simultaneous Localization and Mapping* technic, which allows the robot to map its environment and to calculate its position with the constructed map. Thus, tasks such as surveillance, rescue, mine exploration, firefighting, and so on, could be performed with the support of the proposed mapping.

VII. CONCLUSION

We have proposed a new approach to 3D mapping ofenvironments by a mobile robot with map representation usinga probabilistic occupancy grid. Our approach considers usingthe errors inherent to the robot movement in order to comeup with a better modeling for the mapping algorithm. Visualinformation provided by a stereo vision system are included thathas resulted in a more robust technique where the error can bewell modeled, what is very relevant in robotics decision andapplications.With our proposal, we have the mapping of environmentsactually coherent with sensory data provided by the robotperceptual system. This is one of the main contributions ofour work, besides the manner of using stereo vision for 3Dmapping using occupancy grid. As seen above, this methodhas been tested in applications involving indoor as wellas outdoor scenes and the results show that the resulting mapsare consistent with the environment.

As future work, we are already performing experimentationin more complex environments in order to test the coherentconstruction of 3D occupancy grids. Further, we want to implementour proposal in a SLAM (*Simultaneous Localization and Mapping*) problem, considering its application on bothindoor and outdoor complex environments.

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