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AN IMPLEMENTATION OF THE TRIANGULATION BASED FUSION MAPPING ALGORITHM

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Abstract. This paper examines the mobile robot sonar sensor based environment modelling (map building) problem. The presented approach focuses on environment modelling based on occupancy grid maps and combines the Triangulation Based Fusion algorithm with a bounding box based sonar data correction scheme for sonar reading filtering, outlier rejection and reduction of negative effects caused by uneven sonar sensor placement on the mobile robot body. Described approach is experimentally tested using an ActivMedia Pioneer 2DX mobile robot, so first results are also presented.

Keywords. Robotics, Electric vehicles, Modelling, Sensors.

1. INTRODUCTION

One of the principal research goals in the field of mobile robotics is the development of mobile platforms with the capability of autonomous handling, without intervention by a human operator. A basic prerequisite for such a platform is its ability to percept and build a model (map) of its surroundings. This is achieved by the use of sensors. The sensors most commonly used in mobile robotics for such tasks are sonar's, laser range finders and cameras [1]. Each of these sensor types has its specific advantages and drawbacks. The work presented in this paper focuses on the use of sonar's, because their good range estimation precision and affordable price makes them a solid and very common choice in today's mobile robot applications. The disadvantages of sonar sensors are their poor angular resolution and numerous measurement outliers. The Triangulation Based Fusion (TBF) algorithm [2] is combined with a bounding box correction scheme [5] in order to overcome these disadvantages.

After information about the robot's surroundings has been acquired, a model of the environment i.e. map can be build by fusion of sensor range readings. There are numerous approaches to mapping that use either topological or metric information, or a combination of the two [4]. In this paper, a so-called occupancy grid [3] map is used. In this approach, the environment is tessellated into a two dimensional grid of cells and each cell is assigned a variable. The value of the grid cell variable represents the probability of the cell being occupied by an object. Once acquired, such a map enables the mobile robot to perform navigation tasks like localization, path planning and collision avoidance.

2. SONAR RANGE READINGS

Outliers in sonar readings

As has already been mentioned in the introduction, millimetre precision in range readings and an affordable price ($\sim 10^{\circ}$) make the sonar an attractive sensor in mobile robot applications. However, some major drawbacks, most notably:

- bad angular resolution
- weak echoes
- cross talk
- specular and multiple reflections

can cause numerous outliers in sonar data and greatly limit their reliability. Fig. 1. shows a typical set of raw sonar readings, taken during an experiment in a corridor. The corridor map provided in the background makes it easy to identify the numerous outliers in the sonar data.



Fig. 1. Raw sonar readings.

Mathematical modelling of sonar readings

Different approaches are possible in obtaining a mathematical model of sonar readings. Sonar reading models may vary greatly in their complexity, their ability to take into account various experimentally observed effects, and the amount of information about the environment that they require. A fairly simple stochastic model, previously presented in [2], was used during the course of this work. This model assumes the axial and radial component of a sonar reading to be independent of each other. It then models the axial component with a Gaussian distribution around the returned range reading \overline{r} :

$$r \sim N(\overline{r}, 0.01\overline{r} + 0.01m),\tag{1}$$

and the radial component with a uniform distribution within the main lobe angle:

$$\theta \sim U(-12.5^{\circ}, 12.5^{\circ}).$$
 (2)

The given model gives a fairly accurate qualitative description of sonar range readings and has the big advantage that it requires absolutely no modelling of the environment. As shown in [2], it can be successfully used for modelling uncertainty when building occupancy grid maps.

3. BOUNDING BOX BASED SONAR DATA CORRECTION

The sonar placement problem

In addition to the aforementioned drawbacks, inherent to sonar sensors, further problems may occur due to specific sonar placement configurations on various mobile platforms. The platform used in the experiments presented here, Pioneer2 DX mobile robot, has sonar's more densely placed at the front and back of its body with the sides covered more sparsely (Fig. 2.). This results in poor detection of objects located side wards from the robot. The problem is aggravated by the occurrence of outliers in corridor settings [5].

The bounding box correction method

One way of dealing with the sonar placement problem is the so-called 'bounding box' method, presented in [5]. This approach assumes that the robot is navigating along straight walls, which is a reasonably common situation in office indoor environments, especially in the environment exploration and map-building phase. In this situation, the measurements of the front, back and side sonar pairs are perpendicular to the walls and can be considered reliable i.e. not likely to produce outliers by specular or multiple reflections. Those reliable measurements are then used to form the so-called bounding box, and other measurements are corrected to fit inside the box (Fig. 2.) [5].



Fig. 2. The bounding box creation principle.

It is worth noting that only measurements falling outside of the box are corrected since measurements from within the box may originate from dynamic objects like humans walking by. In Fig. 3., the same set of sonar data is shown as in Fig. 1., only this time the readings are corrected by using the bounding box. By comparing the two figures, a significant improvement due to the bounding box can be observed, as many readings that were previously outliers now correspond to corridor walls.



Fig. 3. Raw sonar data corrected by the bounding box.

The main problem concerning the bounding box method is the relatively strong assumptions it's

making about the environment. Dynamic objects or changes in wall profiles sometimes mean the box constructed of straight lines is poorly representing the actual environment, resulting in outliers among corrected readings. This drawback can be noticed in Fig. 3. when the mobile robot makes a right turn to enter a room at the experiment end.

4. THE TBF ALGORITHM

The triangulation principle and Triangulation Based Fusion (TBF)

To understand the basic triangulation principle, we need to consider two sonar readings originating from the same point in the environment. Due to bad angular resolution, after receiving a single sonar reading we can only assume that there is an object somewhere along the beam arc defined by sensor direction, its main lobe angle and its range reading. However, by combining two readings that have hit a mutual target we can obtain more precise information about the target's position by finding the intersection point of their associated beam arcs. The beam arc intersection point is the first triangulation point estimate.

As the robot moves along its path, more triangulation points are found and further refined by combining subsequent measurements originating from the same target (Fig. 4.). The algorithm is implemented as a sliding time window, where each column represents a complete scan of readings from all sonar's [2]. Each time a new scan is inserted at the window end, the oldest scan is discarded and the window is then swept backwards searching among all past readings for triangulation partners for every reading from the most recent scan. The output of the algorithm is a set of triangulation points, n_t, defined by their position and number of triangulations performed in order to obtain them. Triangulation points supported by a high number of triangulations are highly likely to originate from solid objects in the environment, while sonar readings without triangulation partners are discarded as outliers.



Fig. 4. The TBF principle.

TBF-based occupancy grid mapping

As mentioned earlier, occupancy grid maps are a two dimensional tessellation of the environment into cells. In the most common approach, which's also followed in this paper, all the cells are the same size, forming a uniform grid that represents the robot's surroundings. A variable is assigned to each cell. The value of the variable models the probability of the respective cell being occupied.

By applying a sonar reading probability model, described by equations (1) and (2), to triangulation point computation, we can obtain the uncertainty associated with each triangulation point [2]. Such a refined triangulation point *T*, defined by it's position (x_T, y_T) , triangulation number n_t and covariance matrix **P**_T is suitable for creating an occupancy grid model of the robot's environment (Fig. 5.).

When creating the map, we start off with a grid *G*, consisting of cells $C_{ij} \in G$ (i,j = 1,2,...), and assign a variable $g_{ij} \ge 0$ to each cell. Initially, all cells are assumed to be unoccupied:



Fig. 5. TBF map building.

$$g_{ij} \coloneqq 0, \ \forall C_{ij} \in G .$$
(3)

When updating the map with triangulation point *T*:

$$\left\{ \boldsymbol{n}_{t}, \ \hat{\mathbf{T}} = (\hat{\boldsymbol{x}}_{T}, \hat{\boldsymbol{y}}_{T})^{T}, \ \mathbf{P}_{T} \right\},$$
(4)

we consider the ellipse E, three standard deviations around the triangulation point and the line L, connecting the triangulation point with the last reading that supports it (Fig. 5.). The described mapupdating algorithm is formally expressed as [2]:

 $\forall \hat{T}$, such that $\sqrt{\rho(\mathbf{P_T})} < 0.1m$, update all the cells $Cij \in \{E \cup L\}$ according to the formula

$$g_{ij} = \begin{cases} \max(g_{ij}, A | n_i | f_{ij} \quad \forall C_{ij} \in E \\ \frac{g_{ij}}{2} \quad \forall C_{ij} \in L, C_{ij} \notin E \\ f_{ij} = \frac{1}{\sqrt{2\pi \operatorname{det}(\mathbf{P}_{\mathrm{T}})}} \exp\left(-\frac{l}{2} \left(\left(x_{ij}, y_{ij}\right)^T - \hat{\mathbf{T}}\right)^T \cdot \mathbf{P}_{\mathrm{T}}^{-1} \cdot \left(\left(x_{ij}, y_{ij}\right)^T - \hat{\mathbf{T}}\right)\right) \end{cases}$$
(5)

where $\rho(\mathbf{P}_T)$ is the spectral radius of the covariance matrix and A is a scaling factor that keeps grid values within the desired interval. Since a relatively small number of cells need to be updated for every triangulation point, the computation cost of the algorithm is very reasonable.

5. EXPERIMENTAL RESULTS

In the presented experiments, occupancy grid maps of a real word corridor environment were created, based on triangulation points produced from sonar data by the TBF algorithm. Additionally the bounding box technique for sonar data correction was combined with the TBF algorithm in an attempt to compensate the unfavourable sensor placement. Obtained maps were compared with respect to the presence of artefacts and line segmentation.

By observing the TBF map displayed in Fig. 6., we can see that it gives a fairly accurate and artefact free description of static points in the environment. The main drawback is that it's somewhat segmented i.e. some parts of walls are not detected. By integrating the bounding box approach with the TBF map building method (Fig. 7.), the map segmentation is greatly reduced. However, the reduced segmentation comes at the expense of an increased number of artefacts. Some of the artefacts in the upper part of the corridor are due to a person walking by the robot during the experiment.



Fig. 7. The TBF map with the bounding box.

6. CONCLUSION AND FUTURE WORK

This paper has presented two methods that can be combined with the TBF algorithm in order to build reliable occupancy grid maps of the environment. The effectiveness of these methods in compensating unfavourable sonar placement has been examined by experiments on a Pioneer2 DX mobile robot. A topic for future research is the further improvement of occupancy grid maps by connecting wall segments and rejection of artefacts that don't belong to lined up wall segments.

REFERENCES

- [1] Wolfram Burgard, Armin B. Cremers, Dieter Fox, Dirk Hähnel, Gerhard Lakemeyer, Dirk Schulz, Walter Steiner, Sebastian Thrun, *Expriences with an interactive museum tour-guide robot*, Artificial Intelligence (AI), 114(1-2), pp.3-55, 1999.
- [2] Olle Wijk, *Triangulation Based Fusion of Sonar Data with Application in Mobile Robot Mapping and Localization*, Royal Institute of Technology (KTH) Sweden, PhD Thesis, 2001.
- [3] Alberto Elfes, *Using Occupancy Grids for Mobile Robot Perception and Navigation*, Proceedings of IEEE International Conference on Robotics and Automation, Vol. 2, pp. 727-733, 1988.
- [4] Sebastian Thrun, *Robotic Mapping: A Survey*, Carnegie Mellon University, Technical Report CMU-CS-02-11, 2002.
- [5] Edouard Ivanjko, Ivan Petrović, Kristijan Maček, Improvements of occupancy grid maps by sonar data corrections, Proceedings of 2003 FIRA Robot Soccer World Congress, October 1-3, Vienna, Austria, 2003.

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