UNIVERSITY OF SOUTHERN DENMARK

COURSE PROJECT

ROBOTICS 5TH SEMESTER - FALL 2018

Marble finding robot

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1 Abstract

Contents

2 Introduction

2.1 Problem statement

2.1.1 Problems

The following problems are stated to better describe the focus points throughout the project. XXXX

1. How can an algorithm, which can find marbles in a closed map, be designed?
2. How can this algorithm be optimized, so the robot can find the ball faster, based on previous trails?
3. How can marbles and obstacles be detected from lidar data?
4. How can marbles and obstacles be detected from camera data?
5. How can a Fuzzy-control algorithm be constructed?
6. How can computer vision be used to detect marbles and obstacles, and to construct the map?

XXXX

2.1.2 Limitations

The robot must be able to find marbles in a closed map and optimize itself based on previous trails. Thus the following limitations to the algorithms is listed:

1. To detect marbles and obstacles.
2. To construct a map.
3. To optimize for the shortest distance and time.

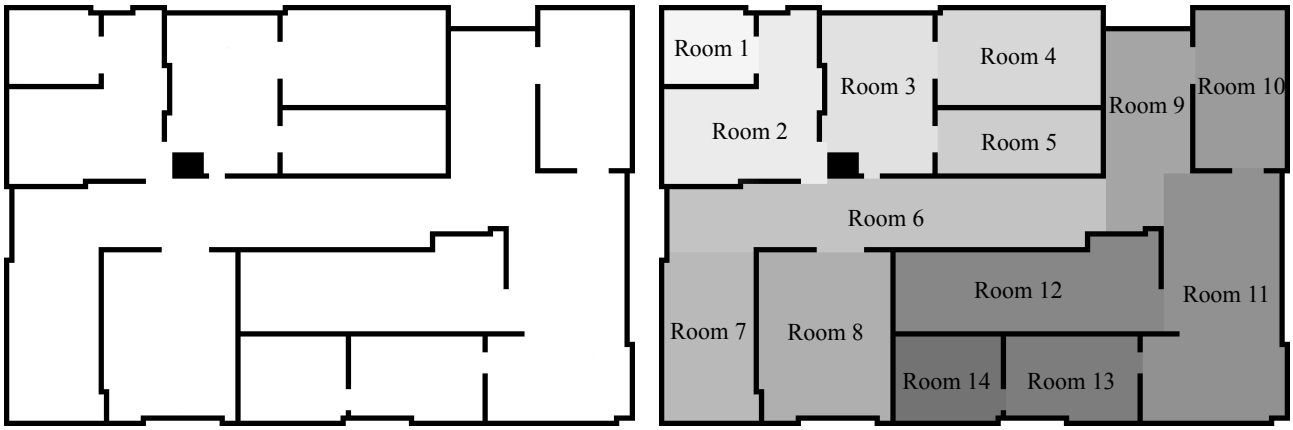
QT Creator, Fuzzy Lite, Gazebo and Matlab will be used throughout the project.

2.2 Readers guide

3 Design

3.1 Environment

The two-wheeled robot should navigate around the environment called “bigworld” shown on figure 1a. To do so, it have been chosen to divide the environment into rooms. The natural definition of *’rooms’* have been taken into account, resulting in a 14 room layout. This can be seen on figure 1b, where each room can be distinguished by different grey scale colours.



(a) Illustration of the world ”bigworld” *(b) ”bigworld” divided into 14 rooms*

Figure 1: Illustration of the world ”bigworld” before and after it has been divided into 14 rooms

The division into rooms are useful in terms of knowing which rooms that have been searched and which that not yet have been searched for marbles.
It is also useful as an abstract state space for reinforcement learning such that it can be found which order the rooms should be visited.

3.2 Line detection

3.2.1 Total Least Square Method

The Total Least Square method uses the normal parametrization of a line in polar coordinates, which is given by the following formula:

$$l: \quad r = x \cdot \cos(\alpha) + y \cdot \sin(\alpha) \tag{3.1}$$

where r represents the distance from the origin to the closest point on the line and α is the angle between the x-axis and the plane normal. This method involves a determination of the orthogonal distance (the shortest distance) from a point (x, y) to a line l (see figure xx). The normal parametrization of the line l_i is given by the following formula:

$$l_i: \quad r_i = x_i \cdot \cos(\alpha) + y_i \cdot \sin(\alpha) \tag{3.2}$$

Missing figure

The separation between those two lines (l and l_i) is given by the difference $d_i = r_i - r$, since both lines have the same α. This means that the orthogonal distance can be described using the following formula:

$$d_i = x_i \cdot \cos(\alpha) + y_i \cdot \sin(\alpha) - r \tag{3.3}$$

This only applies if we assume that there is no noise on the measurements.

The Total Least Square Method solves the problem of fitting a straight line to a dataset of points p with n measurements having errors. The problem of fitting a line can be determined using the following sum:

$$\chi^2\left(l, z_1, ..., z_n\right) = \sum_{i=1}^{n} \left[\frac{\left(x_k - X_k\right)^2}{u_{x,k}^2} + \frac{\left(y_k - Y_k\right)^2}{u_{y,k}^2} \right] \tag{3.4}$$

where (x_k, y_k) are the points coordinates with corresponding uncertainties $(u_{x,k}, u_{y,k})$ and (X_k, Y_k) denote its corresponding point of the straight line l. In the case of fitting the best line to the dataset, minimizes the expression for χ^2 by setting $u_{x,k} = u_{y,k} = \sigma$ and $k = 1, \ldots, n$. This reduces the problem to the Total Least Square method and minimizing is equal to minimizing the orthogonal distance of the measurements to the fitting line. Therefore, in the case of fitting the best line minimizes the expression above to the following:

$$\chi^2\left(l; Z\right) = \sum_{i=1}^{n} \frac{d_i^2}{\sigma^2} \tag{3.5}$$

$$= \sum_{i=1}^{n} \frac{\left(x_i \cos(\alpha) + y_i \sin\ (\alpha) - r\right)^2}{\sigma^2} \tag{3.6}$$

$$= \frac{1}{\sigma^2} \cdot \sum_{i=1}^{n} \left(x_i \cos(\alpha) + y_i \sin\ (\alpha) - r\right)^2 \tag{3.7}$$

A condition for minimizing χ^2 is done by solving the nonlinear equation system with respect to each of the two line parameters (r and α)

$$\frac{\partial \chi^2}{\partial r} = 0 \qquad\qquad \frac{\partial \chi^2}{\partial \alpha} = 0 \tag{3.8}$$

The solution of this nonlinear equation system is determined to the following:

$$r = \overline{X} \cos(\alpha) + \overline{Y} \sin(\alpha) \tag{3.9}$$

$$\alpha = \frac{1}{2} \arctan\left(\frac{-2 \sum_{i=1}^{n} \left[\left(x_i - \overline{X}\right) - \left(y_i - \overline{Y}\right)\right]}{\sum_{i=1}^{n} \left[\left(x_i - \overline{X}\right)^2 - \left(y_i - \overline{Y}\right)^2\right]} \right) \tag{3.10}$$

where $\overline{x}$ and $\overline{y}$ are the means of x and y.

3.2.2 Line Extraction Algorithms

It is usually important for a mobile robot to know its environment. There are several reasons for that, one is that robot must know the location of the obstacles relative to it to avoid driving into them. The environment is predefined in this project, and only has walls as obstacles. These walls can be detected using the robots Lidar sensor and a line extraction algorithm, since all obstacles in the Lidar data can be presented as a straight line. Here, there are several line extraction techniques to choose from. We have chosen to implement the incremental line extraction algorithm, because of its simplicity. The incremental algorithm is shown in table xx.

Table 2: Incremental Algorithm	
1	Start by the first 2 points, construct a line
2	Add the next point to the current line model
3	Recompute the line parameters
4	If it satisfies line condition (go to 2)
5	Otherwise, put back the last point, recompute the line parameters, return the line
6	Continue to the next 2 points, go to 2

Figure 2: Description of the Incremental algorithm

This algorithm implements the Total Least Square method then computing the line parameters. Furthermore, the line model consists of points, which all must comply some line conditions. In that case all points must comply these line conditions. The first condition is a threshold for the angle between the previous and current line model (see figure xx). The threshold is defined to be the following:

$$\theta_{max} = 0,0025$$

The second condition is the angle between two points relative to the robot location (see figure yx). This angle should be greater than this difference, but not twice as great, since this condition should separate the points into two lines, if one point is missing on the list (see figure yy). This angle is therefore defined to be the following:

$$\Delta\theta = (\theta_0 - \theta_1) \cdot 1,25$$

Missing 3 figures

3.3 Marble detection

3.4 Tangent bug

3.5 Search strategy

3.6 Q-learning

Here is something on Q-learning bla bla bla

Algorithm: Q-learning

Algorithm parameters: step size: $\alpha \in$ [0,1], small $\epsilon > 0$
Initialise $Q(s,a)$, for all $s \in S^+$, $a \in A(s)$, arbitrarily except that $Q(terminal, \dot{)} = 0$
Loop for each episode:
    Initialise S
    Loop for each step of episode:
        Choose A from S using policy derived from $Q(e.g., \epsilon - greedy)$
        Take action A, observe $R, S^{'}$
        $Q(S,A) \leftarrow Q(S,A) + \alpha \left[R + \gamma \max_a Q(S',a) - Q(S,A)\right]$
        $S \leftarrow S^{'}$
    until S is terminal

Algorithm: ϵ-greedy policy

if random number < ϵ
    return random action
else
    return policy action

Algorithm: getNextAction()

loop all actions for a given state
    if Q-value is higher than maxValue

4 Implementation

4.1 Line detection

4.2 Marble detection

4.3 Tangent bug

4.4 Search strategy

4.5 Q-learning

5 Discussion

6 Conclusion

Appendices

A Tests

A.1 Room based probability of marbles spawning

The purpose of this test is to determine the probability of a marble spawning in each of the 14 rooms described in section 3.1.

This is done by conduction 50 tests, where the position of each of the 20 marbles in the Gazebo environment are saved resulting in a total of 1000 samples.

Using the class `map_class` the position of the marbles are mapped from gazebo coordinates to pixel positions in the map. That is then used to determine in which room the marbles spawned.

A.2 Basic test

This test is based on value iteration

Figure 3: $dt = 0.1$