UNIVERSITY OF SOUTHERN DENMARK

COURSE PROJECT

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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.

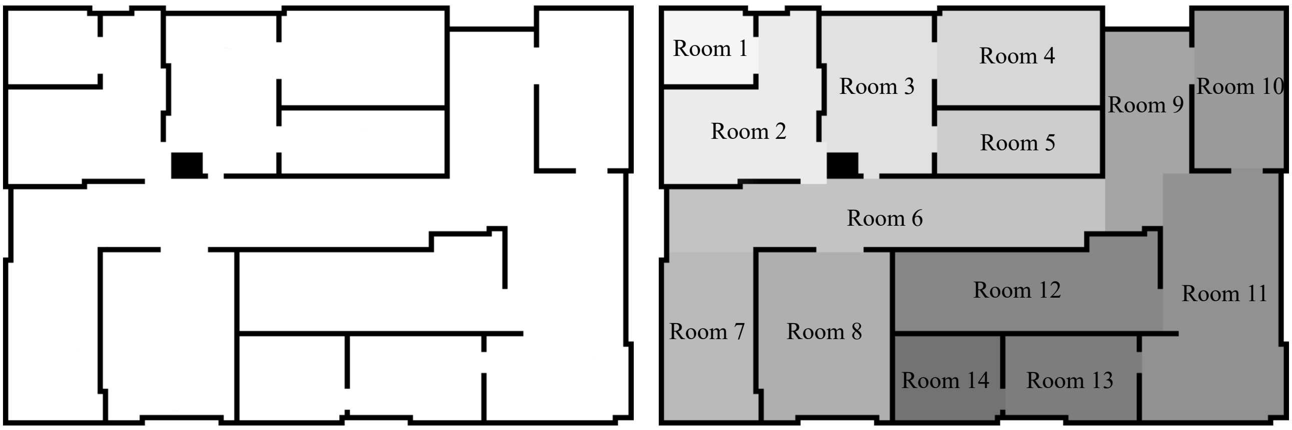
QT Creator, Fuzzy Lite, Gazebo and Matlab will be used throughout the project.

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 Lidar Scanner

The two-wheeled robot given for this project is among other equipped with a 2d lidar (Light Detecting and Ranging) scanner. A lidar scanner detects the distance to targets by emitting a laser pulse and analyzing the time it takes for the beam to reflect and return to its source. The lidar scanner maps the environment and has a detecting range of 10 pixels in Gazebo and a 260 degrees field of view.

The script converts this range into mm by first scaling the pixel map to double size, such that the detecting range is 20 pixels. Afterwards, the script trace the pixel map to a eps-figure using 72 dpi as standard for the postscript. Then, the script converts this range from inches to mm by using a conversion factor of 25.4 mm per inch. This means that this range can be converted into mm by using the following formula:

$$\frac{20\, pixels}{72\; dpi} \cdot 25.4\, \frac{mm}{inch} = 7.06\; mm$$

Now the script scales the world from mm to m, which means that the range of the lidar scanner therefore is 7.06 m.
The lidar scanner maps the surrounding environment by collecting 200 datapoint, which must be processed in order to recognize objects such as walls and marbles. This means that circle and line detecting algorithms must be writing.

The datapoints from the lidar scanner is first visualized by drawing white lines from the robot’s location to each of the 200 datapoints using the `cv::line()` function as shown on figure 2a. Afterwards the datapoints are sorted by checking if the range is equal to max detecting range in order to get the points, that reflects from different object.

The filtered datapoints are drawn as lines upon the unsorted data. These lines can be distinguished by different blue colours depending on the range between the two points ranging from blue to cyan. This blue coloured and white lines are shown on figure 2b.

(a) Illustration of the unfiltered data *(b) Illustration of the filtered data*

Figure 2: Illustration of the unfiltered and filtered data

The two sections below, describes the design of a line and a marble detection algorithm.

3.2.1 Line detection

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 (walls) relative to it to avoid driving into them. In the "bigworld" environment, the obstacles is walls which can be represented as lines from the filtered datapoints. These lines can be represented using a normal parametrization in polar coordinates, 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.

The Total Least Square method assumes that a line can be represented as in equation 3.1. This method also involves a determination of the orthogonal distance (the shortest distance) from a point p_i to a line l as shown on figure 3. The normal parametrization of the line l_i is given by the following formula:

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

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.

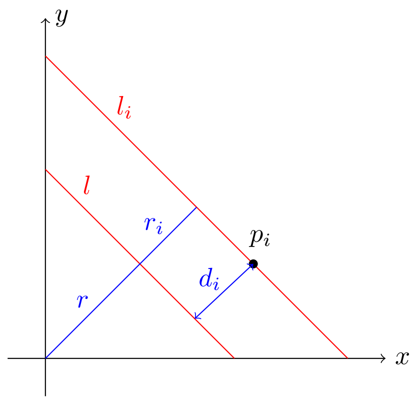


Figure 3: Orthogonal distance from point p_1 to line l

This method gives an solution to 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:

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

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:

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

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

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

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)

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

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.

As explained earlier, the two-wheeled robot should avoid obstacles (walls). To do so, the robot needs to know the location of the walls. It is done by processing the datapoints from the lidar scanner and determining the points which fits to a straight line using a line extraction algorithm. There are several different line extraction algorithms to choose from. The incremental line extraction algorithm is chosen, because it is simple to implement. The pseudo code for the incremental algorithm is shown below.

Table 1: 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

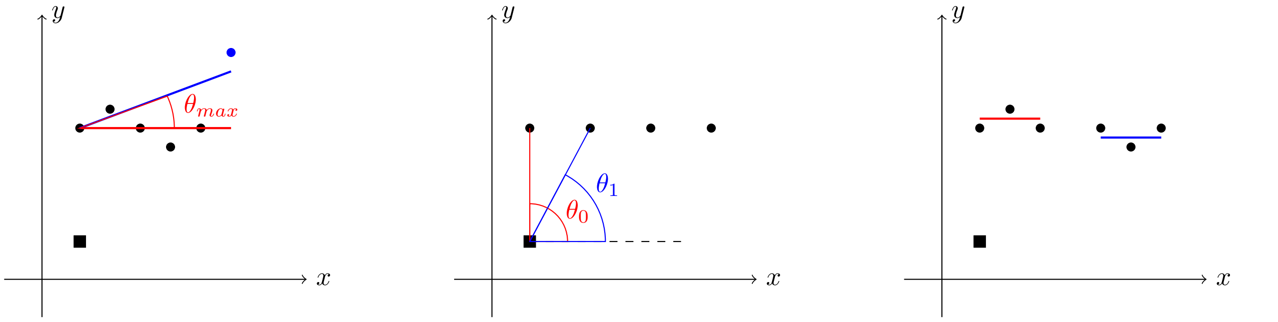
Table 1: Description of the Incremental algorithm

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 conditions. The first condition is a threshold for the angle between the previous and current line model as shown on figure 4a. 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 as shown on figure 4b. 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 as shown on figure 4c. This angle is therefore defined to be the following:

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



(a) Illustration of the angle between current line model (blue line) and previous line model (red line)

(b) Illustration of the angle from horisontal to datapoint relative to the robot

(c) Illustration of the separation of to lines due to a missing datapoint

Figure 4: Illustration of the angle between two datapoints and two line models

3.2.2 Marble detection

3.3 Tangent bug

3.4 Search strategy

3.5 Q-learning

In order to effectively search the environment and collect marbles, a good search strategy must be found. This can be done by utilising reinforcement learning. By using reinforcement learning, the robot can learn from its experience and obtain a good strategy for navigating the environment.

By using a Temporal-Difference learning strategy the optimal action-value function can be estimated by every move taken unlike a Monte Carlo strategy where an episode terminates before any learning is obtained. In some cases with long episodes the Monte Carlo strategy is considered too slow.
Generally there are two categories of Temporal-Difference learning; on-policy and off-policy methods. One of the advantages of an off-policy over an on-policy method are that the action-value function can be estimated independent from the policy being used. The policy only influences which state-action pairs that are visited and updated.

Based on this Q-learning are chosen, the Q-learning method builds on the following update function for updating the action-value function (Q-values).

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t)\right] \tag{3.11}$$

The update function for Q-learning consists of the old value for a given state-action combination plus a scaled difference between the old value, the immediate reward and the maximal value for the next state. The learning rate are denoted α and ranging from 0-1 preferable closer to 0, in order to not to base the policy on this action only. γ denotes the discount factor and are also ranging from 0-1, preferable closer to 1, to ensure that future actions matter.

In the box below, the algorithm for Q-learning can be seen.

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

3.5.1 Definition of states

- Room number
- Vector of boolean values one for each room to know which rooms have been visited
- Boolean for knowing if the state is terminal or not

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

4.1.1 Marble detection

4.2 Tangent bug

4.3 Search strategy

4.4 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.

A.1.1 Description of test

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

These marbles was then mapped to one of the 14 rooms using the class `map_class`. The total amount of marbles found in each room can be seen in table 2. This data was then divided by the total number of marbles, to find the probability.

Due to the fact that the rooms are not the same size, this probability was divided by the size of the room (number of pixels in the map) and the normalised. The result can be ssen in table 3.

A.1.2 Test parameters

- World used	bigworld
- Number of spawned marbles	20
- Number of tests	50

A.1.3 Data

Distribution of marbles	
Total number of marbles found in room 1	5
Total number of marbles found in room 2	65
Total number of marbles found in room 3	75
Total number of marbles found in room 4	52
Total number of marbles found in room 5	72
Total number of marbles found in room 6	158
Total number of marbles found in room 7	17
Total number of marbles found in room 8	118
Total number of marbles found in room 9	100
Total number of marbles found in room 10	22
Total number of marbles found in room 11	75
Total number of marbles found in room 12	160
Total number of marbles found in room 13	47
Total number of marbles found in room 14	34

Table 2: Table of how the marbles are distributed in the 14 rooms based on all 50 tests

Probability of marbles	
Probability of marbles found in room 1	0.012232
Probability of marbles found in room 2	0.061057
Probability of marbles found in room 3	0.078610
Probability of marbles found in room 4	0.059975
Probability of marbles found in room 5	0.117993
Probability of marbles found in room 6	0.098801
Probability of marbles found in room 7	0.019629
Probability of marbles found in room 8	0.099063
Probability of marbles found in room 9	0.114518
Probability of marbles found in room 10	0.027633
Probability of marbles found in room 11	0.044562
Probability of marbles found in room 12	0.130379
Probability of marbles found in room 13	0.072915
Probability of marbles found in room 14	0.062541

Table 3: Table of how the probabilities are distributed in the 14 rooms with room size taken into account

A.1.4 Conclusion

It can be concluded that the highest number of marbles was found in room 12 closely followed by 6 and 8. But due to the size of the rooms, the highest probability is found in room 12, followed by 5 and 9.

A.2 Basic test

This test is based on value iteration

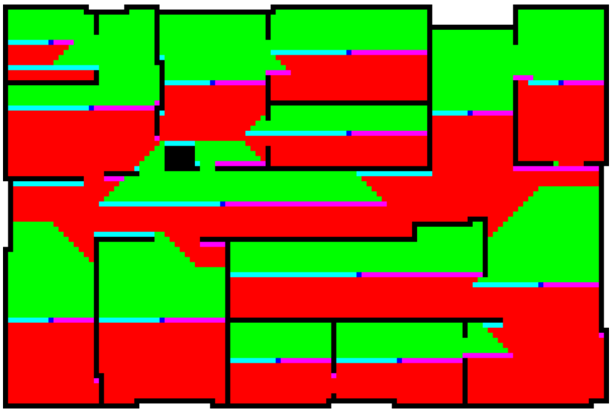


Figure 5: $dt = 0.1$