Assignment 4
Slammin' and Jammin'

Maarten de Jonge
Inge Becht

December 14, 2012

1 Introduction

In this exercise the use of the fastSLAM algorithm is explored for the NXT legorobot. The idea of this algorithm is that the robot makes a map using no a priori knowledge of the environment, while at the same time determining its position in the map. To use SLAM in general, two types of data need to be extracted. Firstly, the robot needs to aqcuire landmarks from the environment. These landsmarks in the case of this assignment are wall corners. To extract these corners the same line extraction algorithm is used as in previous exercises (see assignment 2,3 and 4). Secondly, the robot needs odometry to measure its distance to map the information found by the sensors correctly. This idea has been explored in a previous exercise as well (see assignment 1), but uses a noise distribution to make the next position given the previous one a certaint measure of uncertainty.

Although the outline of the SLAM algorithm is already given, the implementation of both odometry and landmark detection were left open as an exercise. The next section will show what was implemented. After this different experiments were done witht he FastSLAM algortihm to show what paramets can be of a decisive factor when working with a particle filter.

2 The implementation

The implemention of the slam algorithm was given ready made in MATLAB code, and can be run using the function `control_panel.m`. The functions in `FitLine.m` and `predict_odo` still need to be completed.

`FitLine.m` is part of the implementation to find the landmarks for the SLAM algorithm, and as the name suggests the idea is to fit a line given the cluster of input points. First the x,y position of the centroid is found by calculating the mean of the points in the cloud. The orientation of α (We work in pool coordinates) depens on nom and denom, as given in the exercise. Now r can be decided using:

$$r = xcos\alpha + ysin\alpha$$

The x and y values used here are the centroid x and y calculated earlier. Fitline now return the parameters α and r for a possible line in the point cloud.

. The file `predict_odo` tries to predict the new position of the robot given some uncertainty in the covariancy matrix and the sensor values in the wheel. The x and y positions are calculated as follows:

$$x_{t+1} = x_t + dr_n * cos(dth_n + \theta_t)$$
$$y_{t+1} = y_t + dr_n * sin(dth_n + \theta_t)$$
$$\theta_{t+1} = \begin{cases} \theta_t + \theta_d + -2 * \pi & \text{if } \theta_t + \theta_d > \pi \\ \theta_t + \theta_d + 2 * \pi & \text{otherwise} \end{cases}$$

where x_{t+1} is the x position of a particle on time $t+1$, dr_n is a noise parameter that adds uncertainty in the amount of distance driven between each timestep, dth_n is noise parameter for θ and θ_d the difference in theta value between θ_t and θ_{t+1}. Using the `TEST_ODO.m` file a test can be made of the performance of the odometry prediction. In 1 the resulting image given this test can be admired. Unfortunately there was baseline to test our results against, except for the other students getting the same image as we did, as well as the same value for the returned parameter `TOL_JUMP` with a value of 10.5

3 Experiments

Unfortunately we were unable to use the dataset recorded on the Mindstorms robot, so all experiments were done on the provided sample logfile, in which the robot moves forward for a bit through a hallway before turning left and stopping. There the following parameters were available for testing:

- the number of particles

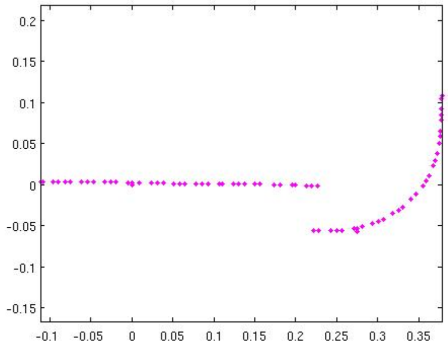


Figure 1: Figure represented byt the `ODO_TEST.m` file.

- the odometry variance in distance (`sigmaX`)
- the odometry variance in angle (`sigmaTH`)
- the range finder variance in distance (`sigmaR`)
- the range finder variance in angle (`sigmaB`)

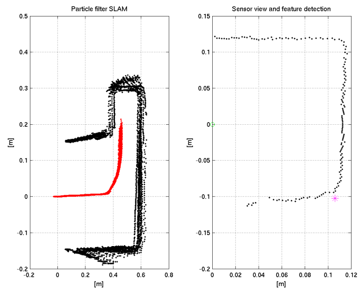
Table 1 shows the combinations of parameters used. A set of default parameters was given and has been used as the baseline. In each trial, one parameter is changed in order to observe its contribution to the result. While the algorithm goes through the data, each particle is drawn and remains visible, showing the path traced by the robot. The detected features are also drawn relative to each particle, leading to kind of a "wall-cloud" showing where a wall might be along with the certainty.

The script used for the experiments can be found in `control_panel.m` on the "experiments" branch of the Git repository.

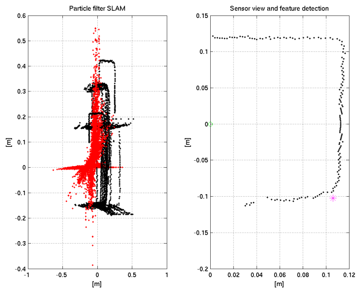
4 Results

Only using a logfile of an unknown environment makes it hard to quantify the output of the algorithm. The final picture output by the algorithm is taken as the result. The left half shows the the locations of every particle over the course of the algorithm in red, and the detected walls in black. The right half shows the sensor input in the last frame, and is irrelevant to the performance of the algorithm. The results are show in figures 2 and 3.

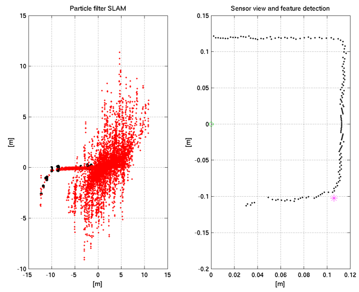
The default parameters lead to a pretty certain localisation, and not much uncertainty in the mapping. Raising the odometry's distance uncertainty leads has a dramatic effect on the end result, rendering it essentially



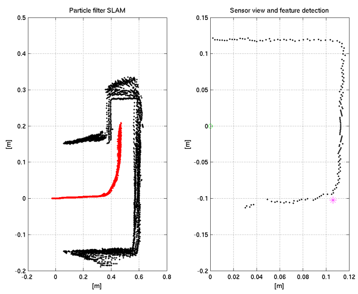
(a) the default parameters



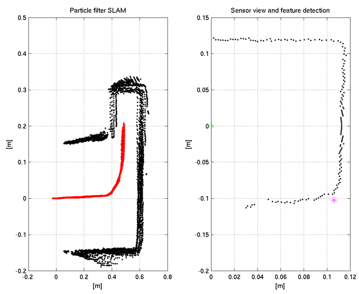
(b) `sigmaX` at 0.05



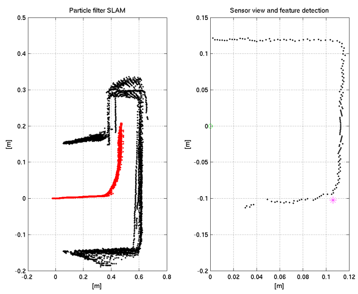
(c) `sigmaX` at 1



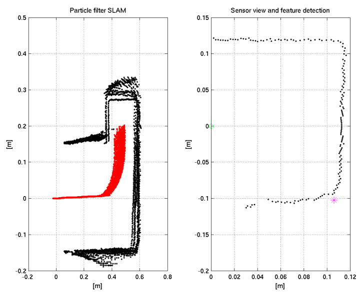
(d) `sigmaTH` at 0.1



(e) `sigmaTH` at 0.5



(f) `sigmaR` at 0.1

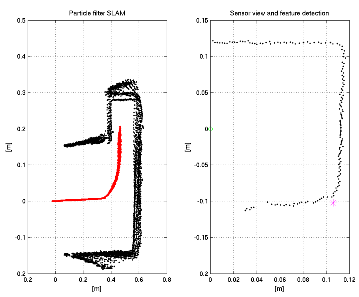


(g) `sigmaR` at 0.5

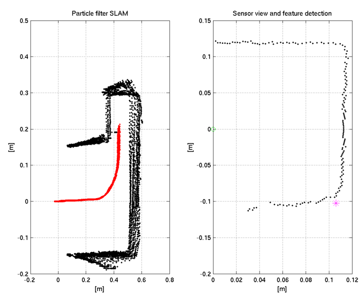
Figure 2: SLAM results, part 1

sigmaX	sigmaTH	sigmaR	sigmaB	particles
0.003	0.02	0.01	0.01	200
0.05	0.02	0.01	0.01	200
0.1	0.02	0.01	0.01	200
0.003	0.1	0.01	0.01	200
0.003	0.5	0.01	0.01	200
0.003	0.02	0.1	0.01	200
0.003	0.02	0.5	0.01	200
0.003	0.02	0.01	0.1	200
0.003	0.02	0.01	0.5	200
0.003	0.02	0.01	0.01	10
0.003	0.02	0.01	0.01	1000

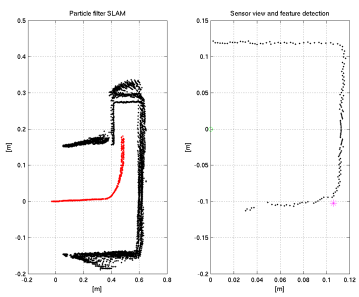
Table 1: The parameters used for the experiments. Each row represents one trial.



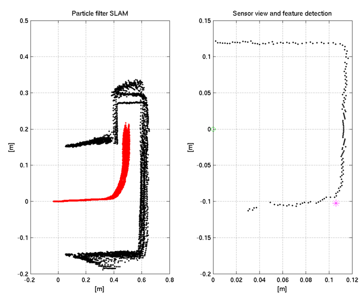
(a) `sigmaB` at 0.1



(b) `sigmaB` at 0.5



(c) particles at 10



(d) particles at 1000

Figure 3: SLAM results, part 2

unusable. The angle variance appears less dramatic, only slightly increasing the uncertainty of the map with no visible influence on the certainty of localisation. In hindsight, parameters tested might have been suboptimal. Because the distance variance is specified in meters and the angle variance in degrees, the chosen parameters are biased in favor the rotation; a 1 meter inaccuracy is far more dramatic than an inaccuracy of 1 degree.

The distance variance in the range finger has a notable effect on the certainty of the robot's location; the path is clearly thicker, with more ambiguity as to the distance of the robot to the wall. The angle variance mainly seems to make the location of the walls slightly more uncertain, without much effect in regards to the localisation.

Surprisingly, the number of particles does little except for deciding the thickness of the red line, which probably means the full extent of the uncertainty is insufficiently represented with only 10 particles, as one could except. In either case, the mapping and localisation are practically the same. Perhaps this is due to the short path travelled by the robot; the number of particles might have a far stronger influence on longer, non-trivial journeys.