

ASSIGNMENT COVER SHEET

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All assessment items submitted in hard copy are due at 5pm unless otherwise specified in the course outline.

Student ID U6329142

For group assignments, list
each student's ID

Course Code ENGN6627

Course Name Robotics

Assignment number Lab4 Part1

Assignment Topic Lab4 Part1

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Tutorial (day and time) Tuesday 12:00-15:00

Word count 1019 Due Date 5th November

Date Submitted 31st October Extension Granted

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- ☐ upholds the principles of academic integrity, as defined in the ANU Policy: [Code of Practice for Student Academic Integrity](#);
- ☐ is original, except where collaboration (for example group work) has been authorised in writing by the course convener in the course outline and/or Wattle site;
- ☐ is produced for the purposes of this assessment task and has not been submitted for assessment in any other context, except where authorised in writing by the course convener;
- ☐ gives appropriate acknowledgement of the ideas, scholarship and intellectual property of others insofar as these have been used;
- ☐ in no part involves copying, cheating, collusion, fabrication, plagiarism or recycling.

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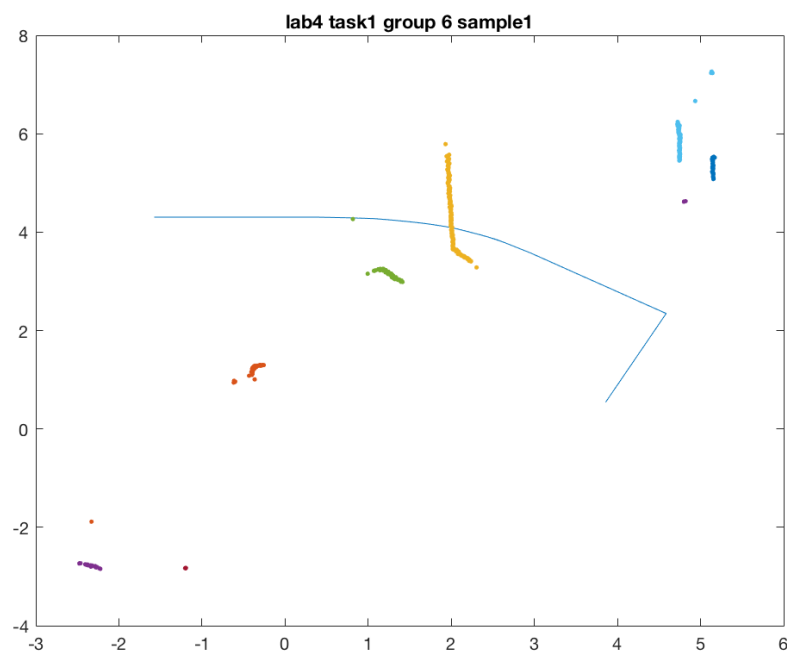
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Lab4 SLAM Part1

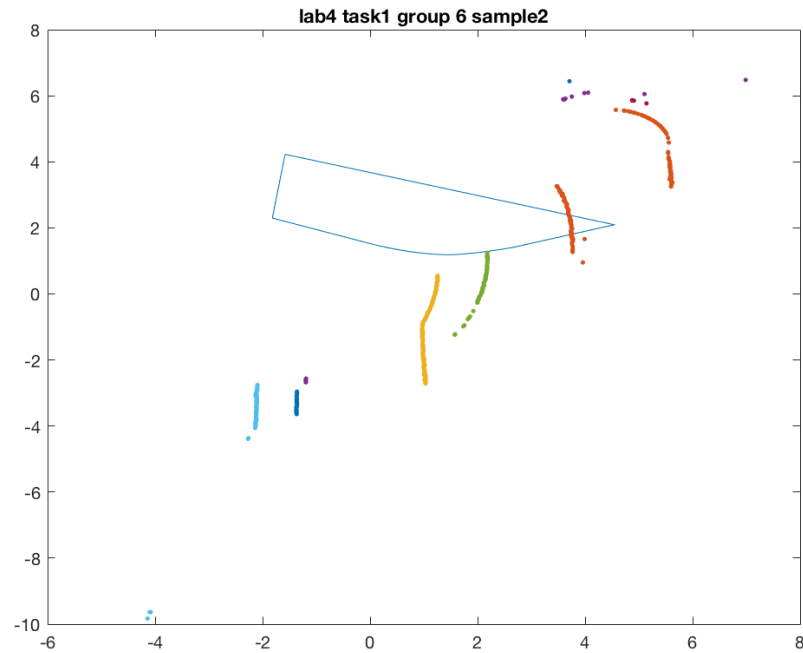
Group: Postgraduate 6

Task 1: Data Acquisition and Plotting

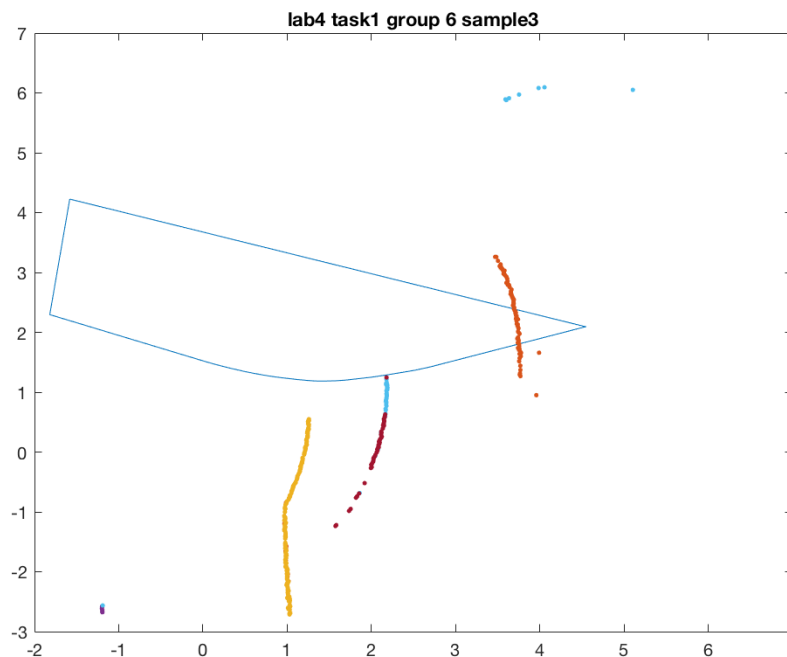
In this task, we need get odometry data and landmark data from the sample bag and then use functions `Relative2AbsolutePose` and `Relative2AbsoluteXY` to translate those data to poses of Robot and Landmark. The python code of this task is in appendix and the name is `lab4_task11`. Then, we extract the data from three sample bags and plot the three graphs separately.



(Fig.1 The pose of Robot and Landmark in sample bag1)



(Fig.2 The pose of Robot and Landmark in sample bag2)



(Fig.3 The pose of Robot and Landmark in sample bag3)

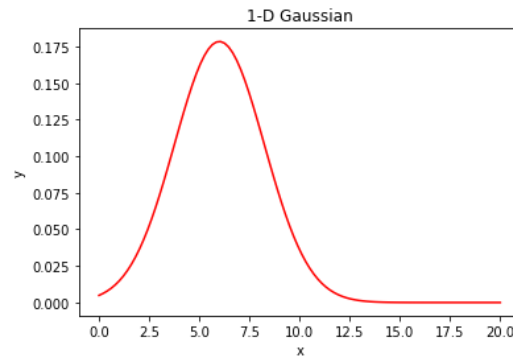
In Fig.1, Fig.2 and Fig.3, the slim blue line is the trajectory of robot. Fig.1's trajectory is still an open loop, Fig.1 and Fig.2's trajectories are close loops, but the curve of the trajectory is also not correct. The different colourful points are landmarks. most landmark points are not a point, there are several lines. It clearly shows that the inaccuracy of the location. Some landmark points are just a point, the reason is that the landmark is away from the trajectory of robot, and robot can just detect it in several frames. Thus, the filters, like Kalman Filter, Particle Filter, must be applied for this data.

Task 2: State Estimation using Filtering

Gaussian Distribution

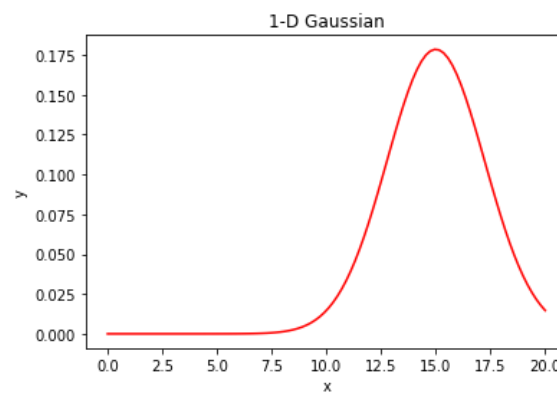
1. 1-D Gaussian Distribution

(1). Mean=6, Variance=5.



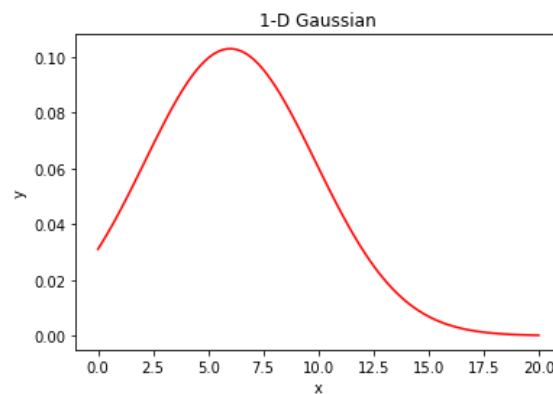
(Fig.4 1-D Gaussian Distribution, $m=6$, $v=5$)

(2). Mean=15, Variance=5.



(Fig.5 1-D Gaussian Distribution, $m=15$, $v=5$)

(3). Mean=6, Variance=15.

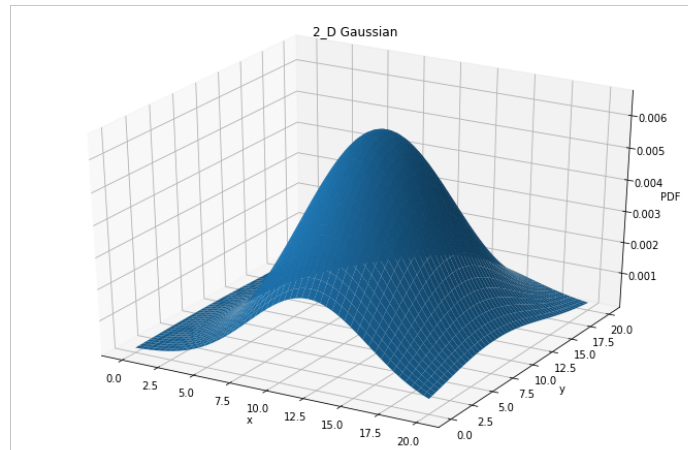


(Fig.6 1-D Gaussian Distribution, $m=6$, $v=15$)

From Fig.4, Fig.5 and Fig.6, we can know that the value of mean is the x position of Gaussian distribution's peak value. And the value of variance will change the shape of Gaussian distribution. When variance increases, the shape of Gaussian distribution will be wider.

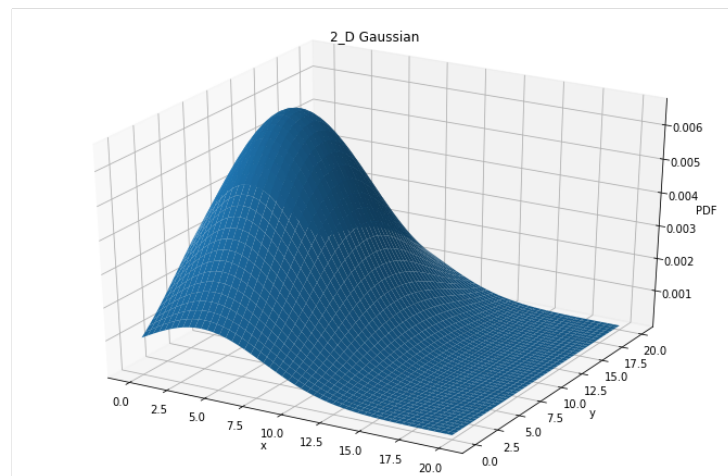
2. 2-D Gaussian Distribution

(1) X-mean=8, Y-mean=12, X-variance=6, Y-variance=4



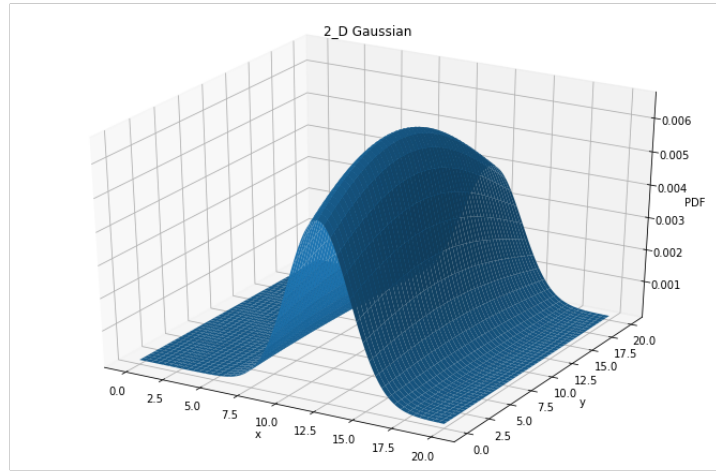
(Fig.7 2-D Gaussian Distribution, x-m=8, x-y=12, x-v=6, y-v=4)

(2) X-mean=10, Y-mean=4, X-variance=6, Y-variance=4



(Fig.8 2-D Gaussian Distribution, x-m=10, x-y=4, x-v=6, y-v=4)

(3) X-mean=8, Y-mean=12, X-variance=12, Y-variance=2



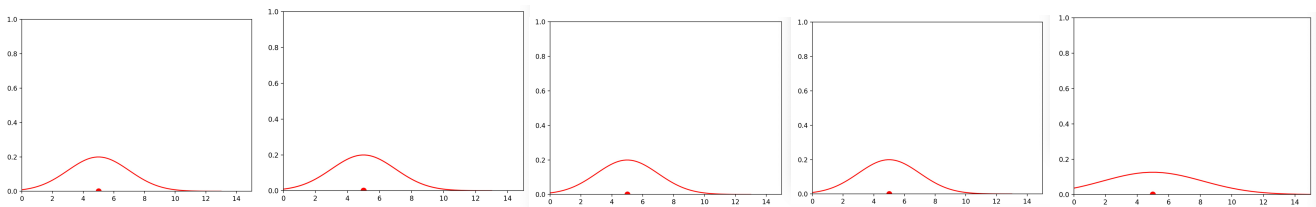
(Fig.9 2-D Gaussian Distribution, $x\text{-}m=8$, $x\text{-}y=12$, $x\text{-}v=12$, $y\text{-}v=2$)

From Fig.7, Fig.8 and Fig.9, the 2-D Gaussian distribution is similar to 1-D gaussian distribution. The values of X-mean and Y-mean will sure the location of Gaussian distribution's peak value in x-y plane. The value of X-variance and Y-variance will change the shape of Gaussian distribution is X and Y directions. When the value of X-variance increases, the shape of Gaussian distribution will be wider in Y direction. When the value of Y-variance increases, the shape of Gaussian distribution will be wider in X direction.

Kalan Filter

1. 1-D Kalan Filter

- (1) Initial position = 0, Initial uncertainty = 10000, Motion error = 2, Measurement error = 4
- (2) Initial position = 10, Initial uncertainty = 10000, Motion error = 2, Measurement error = 4
- (3) Initial position = 0, Initial uncertainty = 100000, Motion error = 2, Measurement error = 4
- (4) Initial position = 0, Initial uncertainty = 10000, Motion error = 10, Measurement error = 4
- (5) Initial position = 0, Initial uncertainty = 10000, Motion error = 2, Measurement error = 10

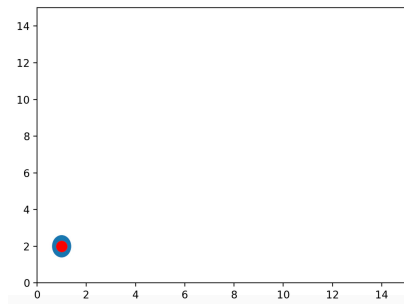


(Fig.10 1-D Kalan Filter for five situations)

Because the figure of Kalan Filter is moving, Fig.10 just show one frame of different situations. We find that the initial position will affect the starting and ending points. Initial uncertainty will affect the shape of trajectory. Motion error will increase the error. Measurement error will affect Kalman gain and covariance.

2. 2-D Kalan Filter

The original set of 2-D Kalan Filter is that $\mu = ([0, 0], [0, 0])$; $\text{sig} = ([1000, 0], [0, 1000])$; measurement error = $([0.78, 0], [0, 1.22])$; motion error = $([2.1, 0], [0, 1.5])$.

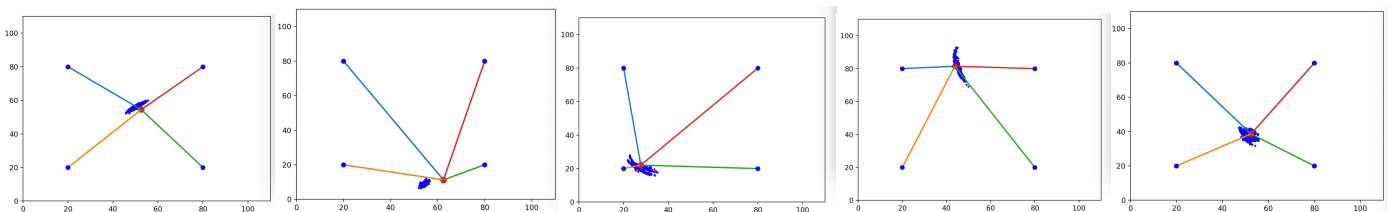


(Fig.11 2-D Kalan Filter in original data)

The result of 2-D Kalan Filter is similar to 1-D Kalan Filter. When we change the initial position, initial and end points will change. Changing initial uncertainty will make uncertain about the initial position and influence the covariance. Changing measurement error and motion error will have an effect on the covariance matrix.

Particle Filter

- (1) Forward noise = 0.05 turn noise = 0.05 sense noise = 5.0 N = 1000
- (2) Forward noise = 0.2 turn noise = 0.05 sense noise = 5.0 N = 1000
- (3) Forward noise = 0.05 turn noise = 0.2 sense noise = 5.0 N = 1000
- (4) Forward noise = 0.05 turn noise = 0.05 sense noise = 10 N = 1000
- (5) Forward noise = 0.05 turn noise = 0.05 sense noise = 5.0 N = 10000



(Fig.12 Particle Filter of five situations)

Fig.12 shows that the final position of five different parameters sets in number (1), (2), (3), (4) and (5). When the forward noise and turn noise increase, there are more noise in final state. Sense noise will affect the filter in the whole process. Large number of particles will increase the sample size and the accurate. However, if the number is large enough, the error will not be improved.

Question 1: Theory

1. Bayesian formula

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

A and B are events and $P(B)$ does not equal zero.

2. Total probability theorem

Given n mutually exclusive events A_1, \dots, A_n whose probabilities sum to unity, then

$$P(B) = P(B|A_1)P(A_1) + \dots P(B|A_n)P(A_n)$$

where B is an arbitrary event, and $P(B|A_i)$ is the conditional probability of B assuming A_i .

3. Markov assumption

the state X_t only depends on the previous state X_{t-1}

$$p(x_t | x_{1:t-1}, z_{1:t}, u_{1:t}) = p(x_t | x_{t-1}, u_t)$$

4. SLAM

Simultaneous localization and mapping (SLAM) is the computational problem of constructing or updating a map of an unknown environment while simultaneously keeping track of an agent's location within it.

5. Multivariate distributions

Given more than two variables, x, y, z, \dots , that are defined as a probability space, the multivariate distribution for x, y, z, \dots is a probability distribution that gives the probability that each of x, y, z, \dots falls in any particular range or discrete set of values specified for that variable.

Question 2: Gaussian Motion Model

1. a). The equations are below:

$$\overline{bel}(x_t) = \sum_x p(x_t | u_t; x_{t-1}) bel(x_{t-1})$$

$$\mu_{prior} = \mu_{posterior} + \mu_{move}$$

$$\sigma_{prior}^2 = \sigma_{posterior}^2 + \sigma_{move}^2$$

Thus, $\mu_{prior} = 2 + 1 = 3$, $\sigma_{prior}^2 = 16 + 4 = 20$.

$$\text{b). } \mu_{prior} = \frac{2}{1} + \frac{1}{1} = \frac{3}{2}, \sigma_{prior}^2 = \begin{vmatrix} 2 & 1 \\ 1 & 4 \end{vmatrix} + \begin{vmatrix} 2 & 0 \\ 0 & 1 \end{vmatrix} = \begin{vmatrix} 9 & 6 \\ 6 & 18 \end{vmatrix}$$

2. We know that $p(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1(x-\mu)^2}{2\sigma^2}}$, to calculate Z, which is also a Gaussian distribution.

$$p(Z) = p(\omega_1 X + \omega_2 Y) = \frac{1}{\sqrt{2\pi(\omega_1^2 \sigma_X + \omega_2^2 \sigma_Y)}} e^{-\frac{1(Z - \omega_1 \mu_X + \omega_2 \mu_Y)^2}{2(\omega_1^2 \sigma_X + \omega_2^2 \sigma_Y)}}$$

Then, we can calculate that $Z \sim N(\omega_1 u_1 + \omega_2 u_2, \omega_1^2 s_1 + \omega_2^2 s_2)$.