# THE EFFECTS OF VARYING NOISE PARAMETERS ON EKF-SLAM

Cody Cripps

N9945008

Queensland University of Technology

EGB439 Advanced Robotics

## 1. INTRODUCTION

EKF SLAM is a flavour of simultaneous localisation and mapping (SLAM), which utilises the extended Kalman Filter. This system treats the locations of landmarks and the system itself, as gaussian distributions. This system was popular in the 1990s through to the 2000s until the development of FastSLAM.

EKF SLAM also assumes that noise is gaussian, which causes the system to be vulnerable to uncertainty, which can then result in a breakdown of the systems linearisation. This report aims to investigate the effects of changes in the assumed noise parameters, for the prediction and update steps; R and Q respectively.

# 2. APPROACH

To investigate these parameters a control dataset was required, which would contain:

- The ground truth robot location data,
- The output of the robot's encoders for the prediction step,
- And the output of the robot's sensing.

This data was obtained by 'hardcoding' the robot to move in a circle, while storing the global localisation data, as well as the sense data.

Using this data the effects of the R and Q parameters were tested.

## 2.1. Prediction Noise → R

The R matrix represents the assumed Gaussian noise in the prediction step. This means that greater values in this matrix make the algorithm less likely to "trust" the prediction model being used.

This was initialised in MATLAB as:

```
R = diag([dN thetaN]).^2;
```

Where: dN → Noise in the predicted change in distance.
thetaN → Noise in the predicted change in angle.

## 2.2. Update/Sensor Noise → Q

The R matrix represents the assumed Gaussian noise in the prediction step. This means that greater values in this matrix make the algorithm less likely to "trust" the prediction model being used.

The Q matrix represents the noise in the data gathered from the sensor. Therefore changes in this change how much the algorithm updates it's position based on each landmark it sees.

This was initialised in MATLAB as:

```
Q = diag([dN thetaN]).^2;
```

Where: dN → Noise in the sensed distance to any landmark
thetaN → Noise in the sensed angle of a landmark.

# 3. Testing

## 3.1. R Distance Noise:

For this test the following parameters were set

Q = diag([0.5 20*pi/180]).^2 = [0.25, 0; 0, 0.1218]

R = diag([dN 0.01*pi/180]).^2;

With dN = 0.15, 0.1, 0.05, and 0.01

This test was run for half of the data as beyond this point the effects of Q are more prevalent.

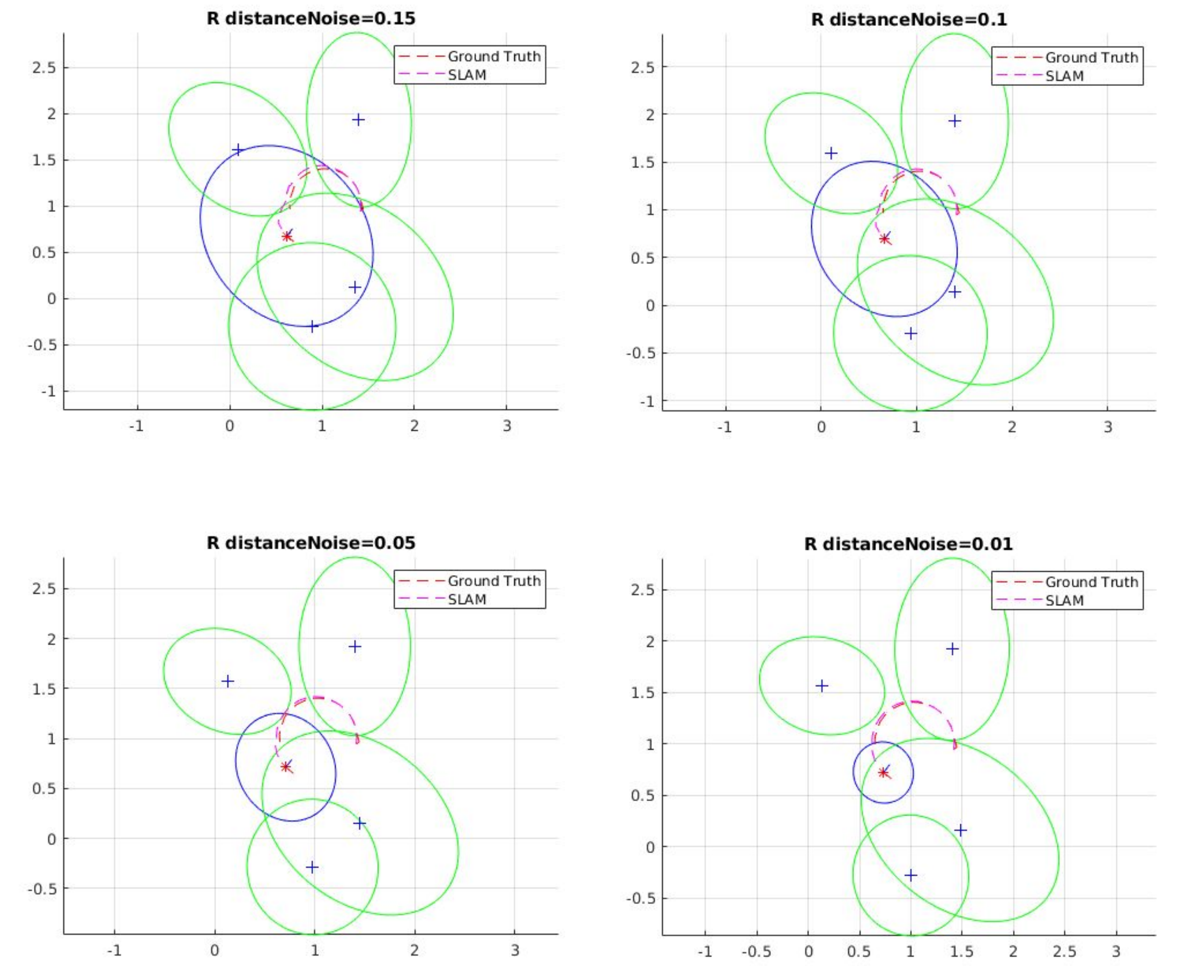


Figure 1: Effects of varying distance noise in the prediction step.

## 3.2. R Angle Noise:

For this test the following parameters were set

Q = diag([0.5 20*pi/180]).^2 = [0.25, 0; 0, 0.1218]

R = diag([0.01 thetaN*pi/180]).^2;

With thetaN = [1,5,10,25]

This test was run for even less time, to set a focus on just the effects of rotation.

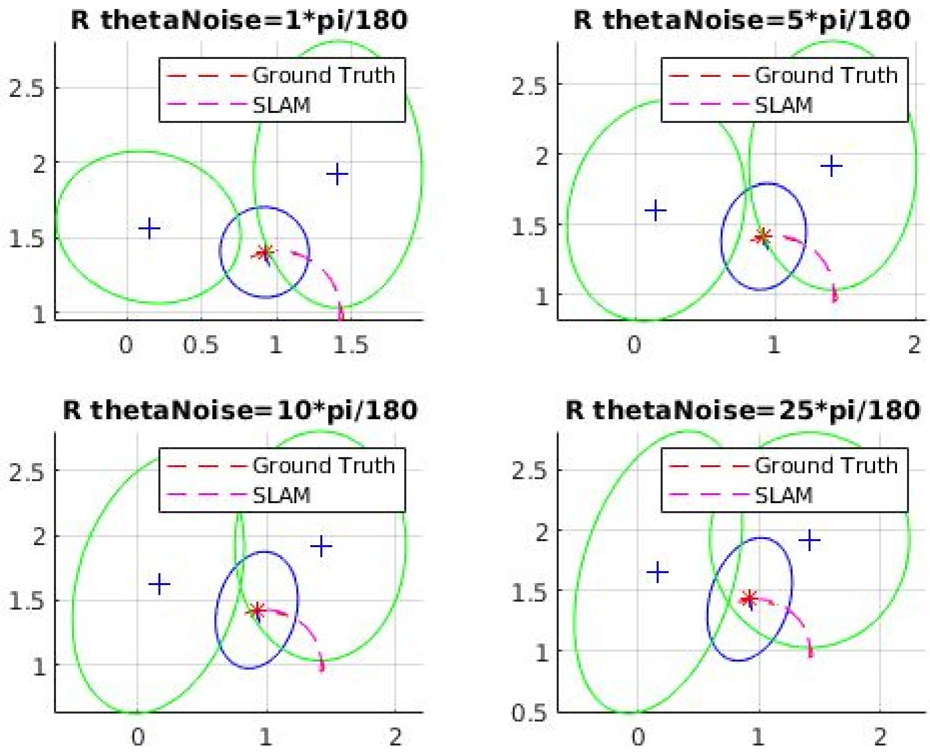


Figure 2: Effects of varying angle noise in the prediction step.

## 3.3. Q Distance Noise:

For this test the following parameters were set

R = diag([0.01 1*pi/180]).^2 = [1e-4, 0; 0, 3.046e-4]

Q = diag([dN 15*pi/180]).^2;

With dN = [1, 0.5, 0.25, 0.1]

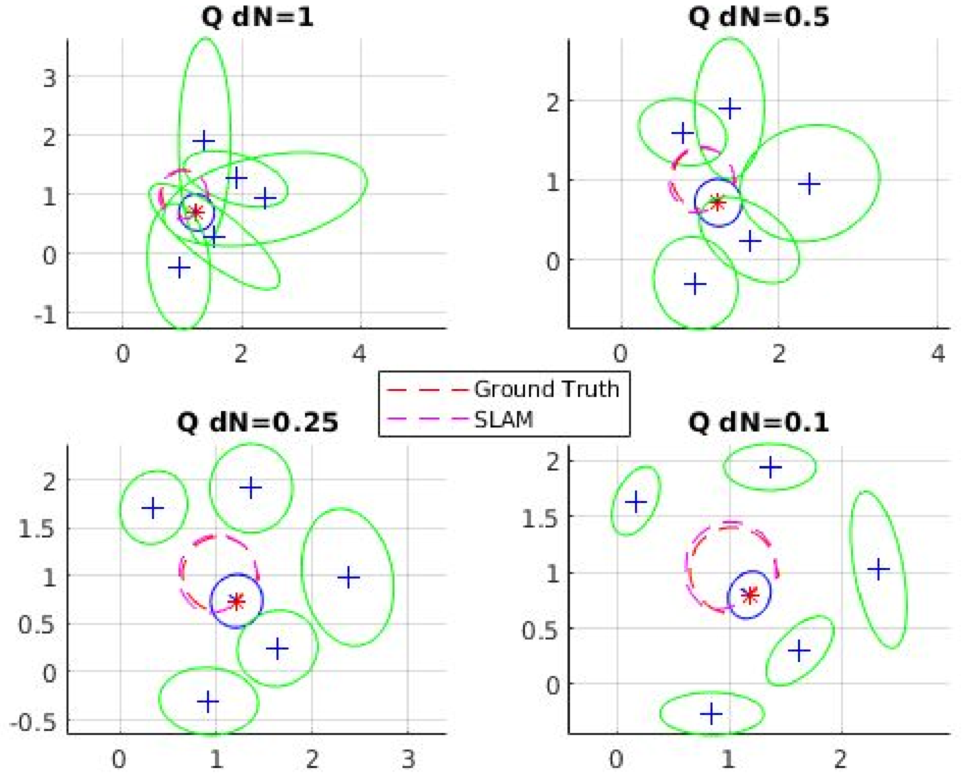


Figure 3: Effects of varying distance noise for sensing/update.

## 3.4. Q Angle Noise:

For this test the following parameters were set

R = diag([0.01 1*pi/180]).^2 = [1e-4, 0; 0, 3.046e-4]

Q = diag([0.01 thetaN*pi/180]).^2;

With thetaN = [30,15,10,5]

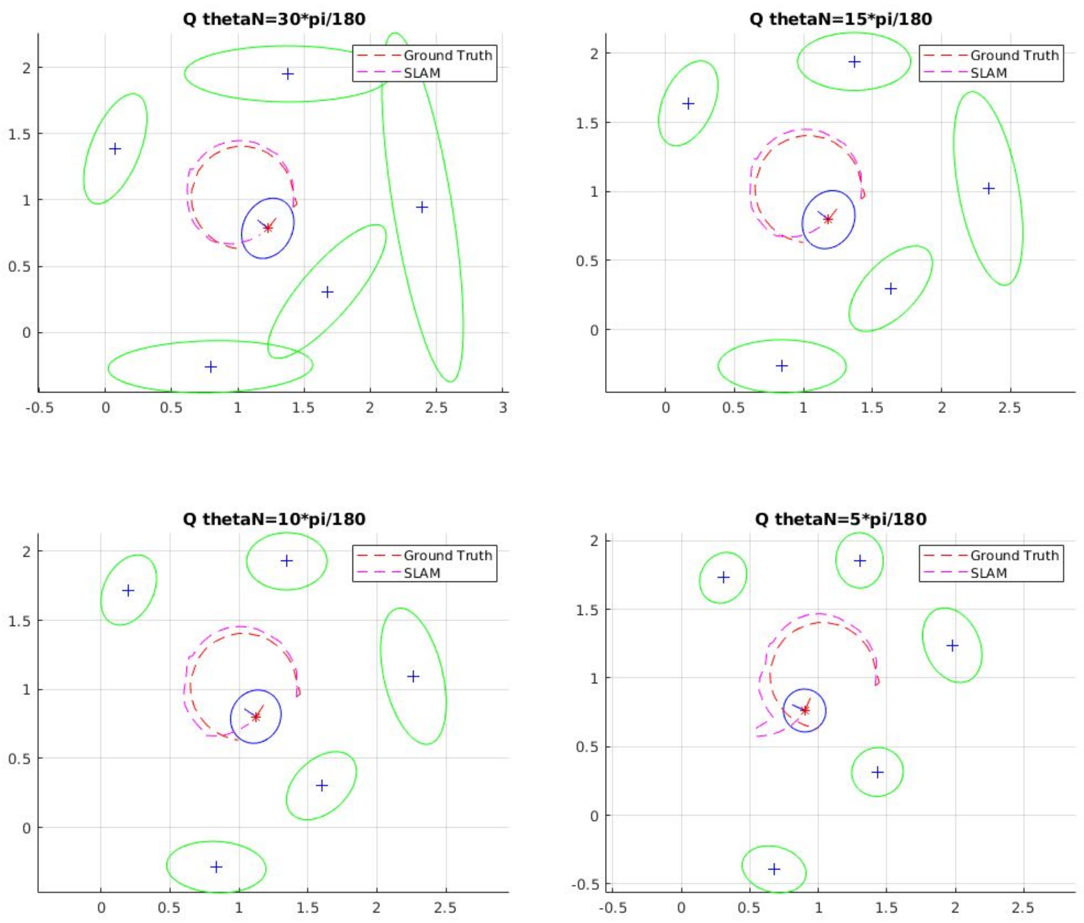


Figure 4: Effects of varying angular noise for sensing/update.

# 4. Discussion

It can be seen in figure one that with a decrease in the distance noise for the prediction, there is a proportional decrease in the overall magnitude of uncertainty of the robot's position. The is as with lower noise on the distance the algorithm believes itself to be more certain about it's position in both the x and y direction.

Figure 2 shows that increases in the noise assumed for the angular prediction causes the covariance to elongate. This makes sense as with a higher uncertainty here it isn't clear by how much the robot has rotated, therefore requiring a more varied range perpendicular to the forward direction prior to rotation.

It can also be seen that neither of these had any effect on the uncertainty of the beacons, as the beacons are assumed to be stationary and are therefore not affected by the prediction step.

In figure 3 it can be seen that by decreasing the assumed noise in the distance measurement of the sensor, the effect of further readings of the landmarks after their initialisation is reduced. In this case this is seen by smaller certainties on the landmark positions and their layout resembling the real layout more when the distance noise is smaller.  This noise also changes how much the robots position is affected by the reading of a known landmark. It can also be seen that the magnitude of uncertainty on the landmarks is directly proportional to the dN for sensing.

It can be seen in figure 4 that, as it was for angular prediction noise, higher angular noise in sensing elongates the covariances of each feature of the system. This elongation in this case is more prevalent in the landmarks as these are more reliant on the sensing system than the robot state.

From the results above it can also be concluded that the encoders and prediction step were more effective than the implimented sensing system, as when the prediction step had more control (lower R parameters and higher Q), the SLAM output was more similar to the ground truth.

# 5. Conclusion

The R matrix had a clear effect on the systems ‘trust’ in the odometry predictions. This manifested as smaller covariances on the robot with lower noise parameters for R. Similarly Q acted as a measure of trust for the sensing system, which manifested as reduction in covariance for the beacons with lower noise parameters for Q. The angular noise parameters for both Q and R can be seen to cause elongation of the covariance as they increased, which was attributed to less certainty in the effect of rotation and therefore a larger range of possible locations perpendicular to the rotation. The distance noise parameter in the case of R resulted in a smaller overall magnitude for the covariance of the robot, and  more importantly better tracking of the true path of the robot, which implies that the encoders were more accurate than the sensing information. Further to support this point, it was seen that a reduction in the distance noise parameter for the sensing also increased the accuracy of the estimated path.