Lab4 - EKF Map Based Localization

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1 Introduction

The objective of this lab is to implement an Extended Kalman filter(EKF) to localize the turtlebot in simulator. The environment and the motion of the robot are provided. Also, the package of split and merge from lab2 is used to sense the lines(walls in the environment).

The Extended Kalman Filter is an extension of Kalman Filter, which can be termed as a non-linear case of the Kalman Filter. EKF localization estimates the state of the robot including position and orientation as it moves and senses the environment. It works by estimating a probability distribution over the robot state each time the robot senses the environment. Like the particle filter, EKF also includes the prediction and calibration of the prediction steps. The probability distribution of the robot state can be shrunk every time the robot receives new measurement.

2 Algorithm and Implementation

EKF is a recursion that provides the "best" estimate of the state vector. It contains three parts which are prediction, data association and Update of the state of robot.

2.1 Prediction

The initial state of the robot is always known. For every movement of the robot, its pose is predicted based on its odometry. Ideally, the state of the robot is the addition of the last state and its displacement. In the real situation, it has uncertainty along with the state and the displacement.

So, the prediction step is mainly divided into two parts. One is the prediction of the state, the other one is the prediction of the uncertainty. The uncertainty of the state is represented as an ellipse in the map and it's expanding while robot moving since there's no update for it. The prediction of the state is adding the mean of the uncertainty to the last state. If the robot and the movement are not referring to the same frame, it is not a linear addition but has to use the comp() function to deal with the non-linear addition. The prediction of the uncertainty is adding the covariance of the noise to the existing uncertainty. For non-linear case, the parameters can be obtained by taking the partial derivative of the state vector.

2.2 Data association

Data association is a significant part of EKF. It provides correct and meaningful data for the update step for accurate localization. It mainly matches the sensed lines with the given map. The Manhattan distance is used to decide if the sensed lines and the map are close enough and matched. And the chi-square test threshold is set to do the determination. In addition, the sensed lines and the map should be converted to same reference frame to be compared.

The optional part of avoiding sensed lines to match "ghost" walls is done by comparing the lengths of the sensed line and the map. Only the pairs of which sensed lines are shorted than the map lines are taken into account.

2.3 Update

After obtaining the match from data association, the difference between measured features and the expected features can be computed which is the innovation. The uncertainty of the innovation is computed for updating the state of robot. The state then is updated by operating with the Kalman gain K.

In this step, there's more than one observation used for updating the state which can be more accurate.

3 Results

3.1 Prediction

The following figures show the progress of prediction step. The ellipse represents the possible positions of the robot. As we can see, without the knowledge of the sensed environment and the calibration of the prediction, the probability distribution of the robot state is large and expanding as the robot moving.

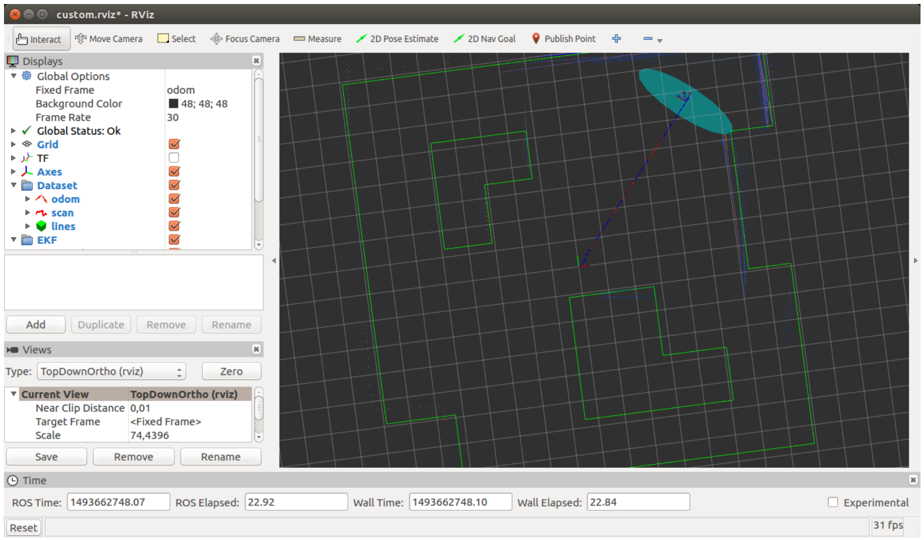

Figure 1: The prediction of the robot state shown in blue ellipse

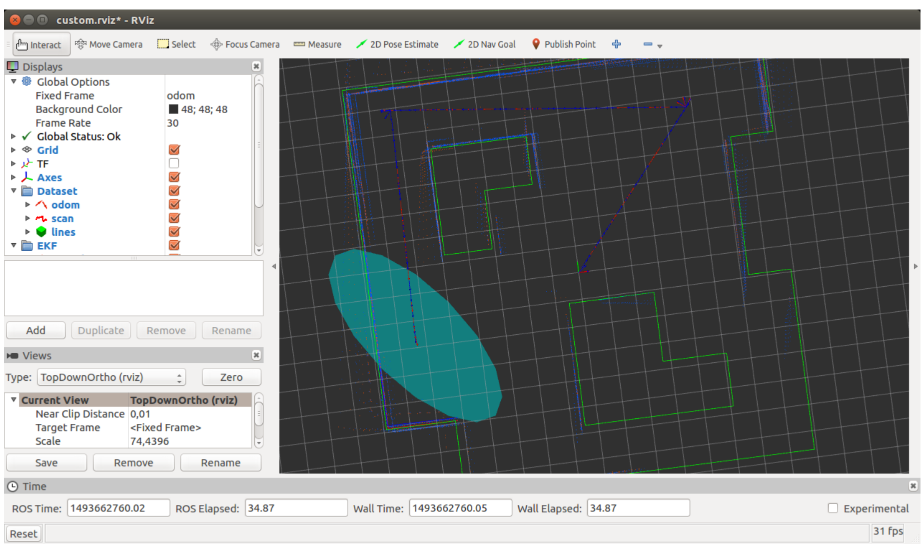

Figure 2: The prediction of the robot state shown in blue ellipse

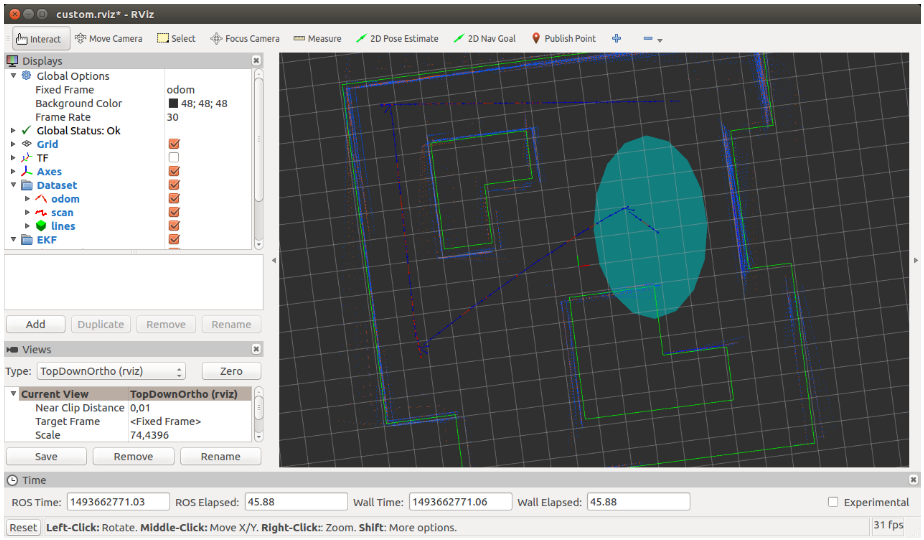

Figure 3: The prediction of the robot state shown in blue ellipse

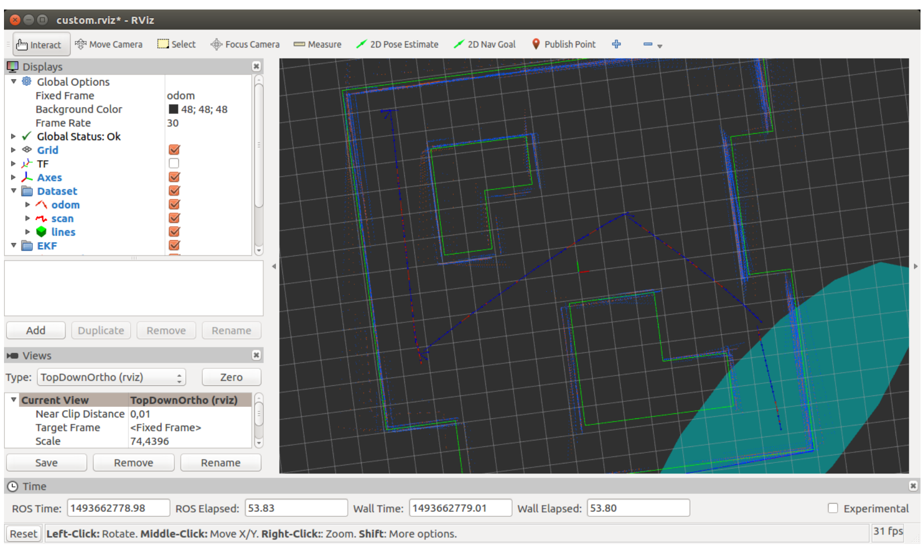

Figure 4: The prediction of the robot state shown in blue ellipse

3.2 Update

The following figures show the possible location of robot using prediction and update of the state. As we can see, the ellipse is much smaller than the previous ones. That means the robot is localized more accurately. As the robot moving around, the probability distribution is growing but shrinking when the robot senses the environment and obtains the measurement.

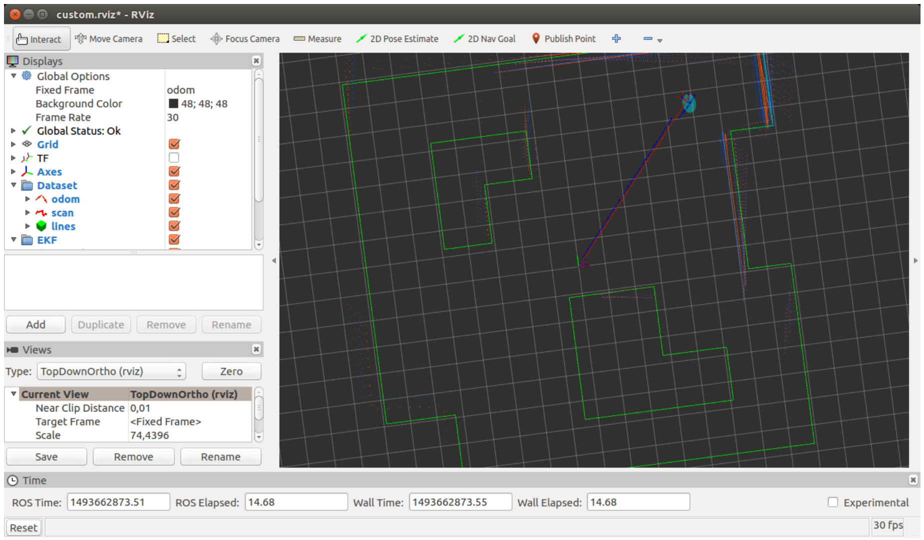

Figure 5: The possible state with prediction and update

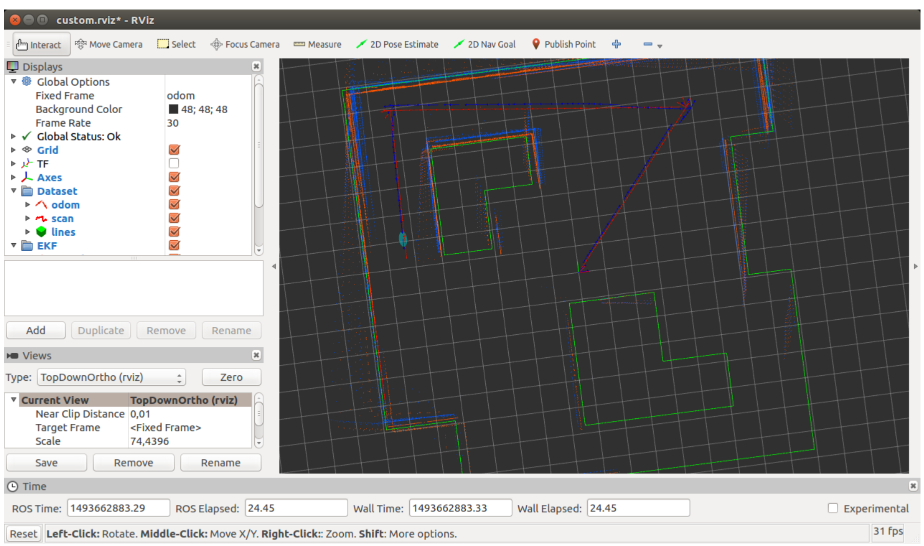

Figure 6: The possible state with prediction and update

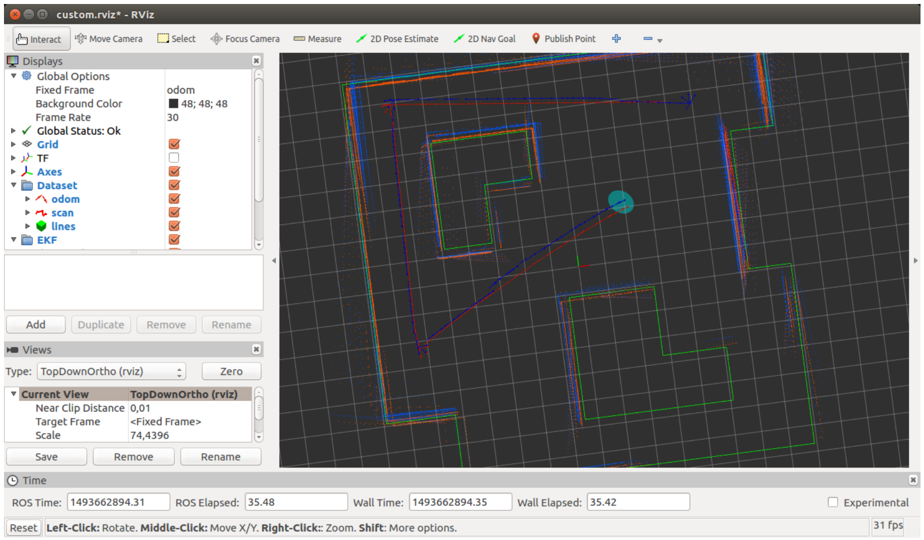

Figure 7: The possible state with prediction and update

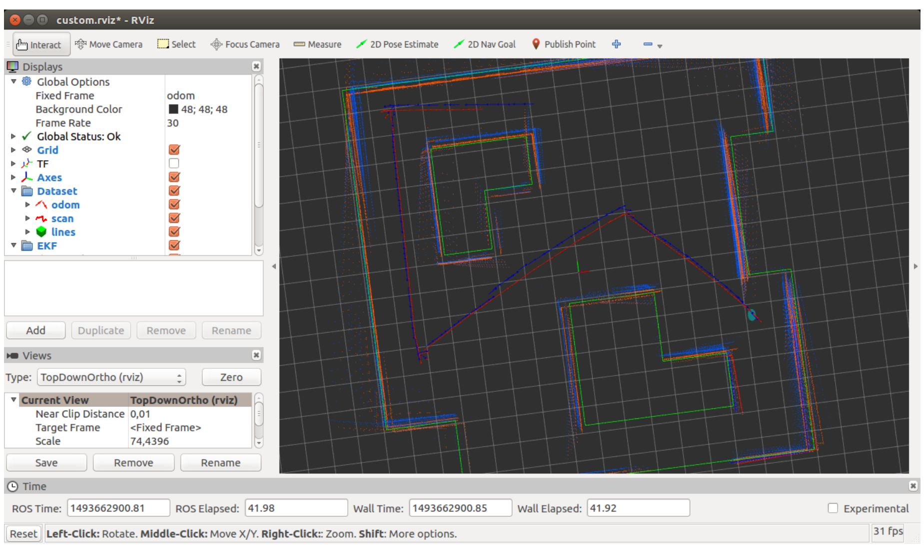

Figure 8: The possible state with prediction and update