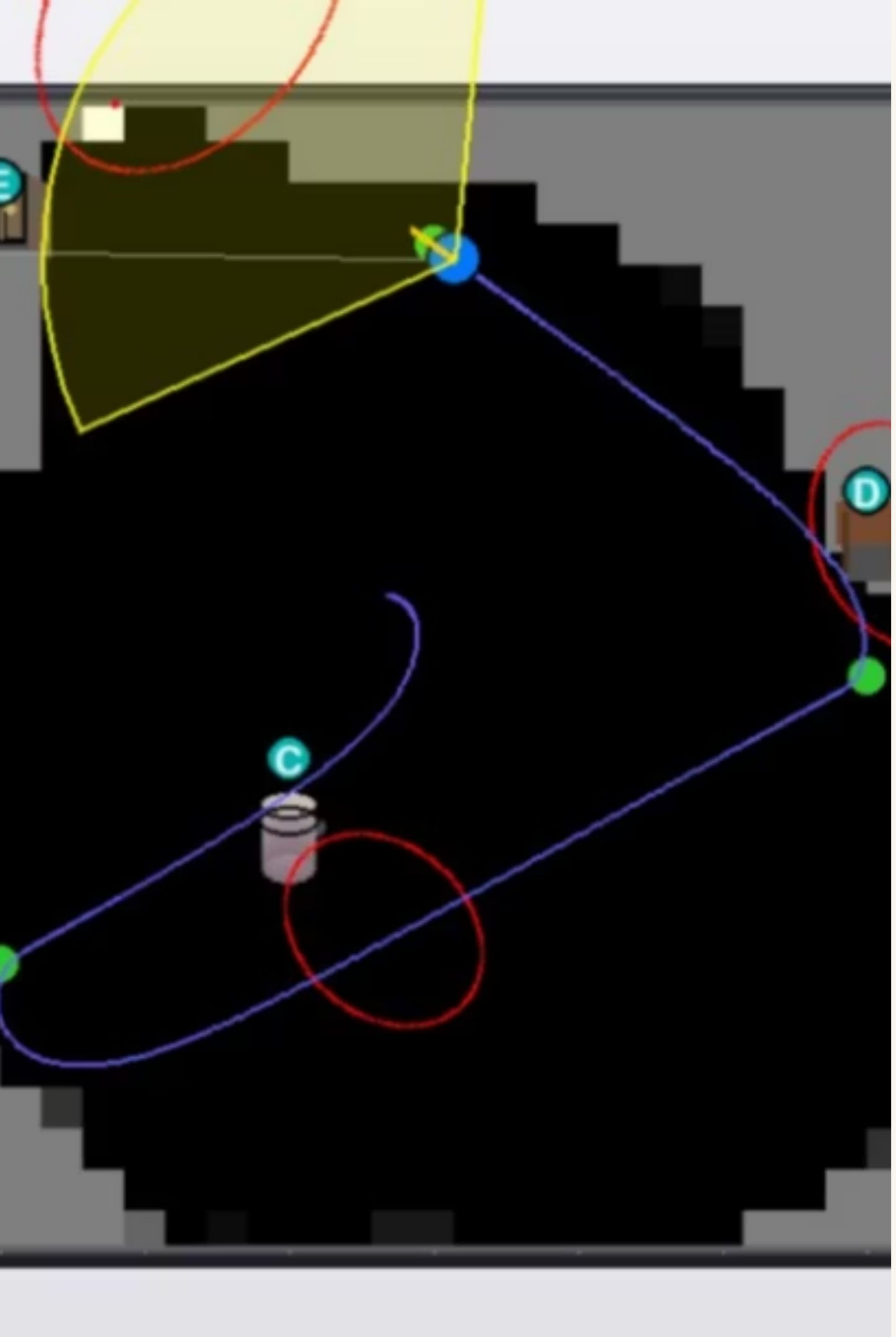

EKF-SLAM for a Differential-Drive Mobile Robot

A Camera-Based EKF-SLAM Approach with Autonomous Navigation

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Motivation: Navigating Unknown Environments

Autonomous Operation

Autonomous robots require the ability to operate effectively within unknown environments, demanding real-time understanding of their surroundings.

Sensor Imperfections

Traditional odometry and sensor readings are inherently noisy and uncertain, leading to drift over time.

The SLAM Principle

Simultaneous Localisation and Mapping (SLAM) addresses these challenges by solving two coupled problems:

- Robot Localisation (estimating robot's pose)
- Environment Mapping (building a map of landmarks)

Probabilistic Framework

The Extended Kalman Filter (EKF) provides a robust probabilistic framework for managing uncertainties in non-linear systems inherent to SLAM.

Problem Definition: Indoor Navigation Challenge

1

Confined Environment

The scenario involves a 10m x 8m indoor space, typical of many autonomous robot applications.

2

Unknown Start

The robot begins with an unknown initial pose, adding complexity to the localisation task.

3

Fixed Landmarks

Five fixed landmarks are present in the environment, serving as critical reference points for mapping.

4

Noisy Sensors

Both odometry and the range-bearing camera introduce noise, simulating real-world sensor limitations.

5

Autonomous Goal

The robot's mission is autonomous navigation through three pre-defined waypoints.

6

Simultaneous Goal

The ultimate goal is the simultaneous estimation of robot pose and the mapping of the environment.

Robot Model & Motion Control

Differential-Drive Robot

Our robot model is a differential-drive system, characterised by:

Linear velocity v

Angular velocity ω

Waypoint Tracking Controller

Navigation is achieved via a controller that minimises:

Distance error de

Heading error θe

Control Laws

$$v = K_d d_e$$

$$\omega = K_\theta \theta_e$$

EKF-SLAM: Joint State Representation

Unified State Vector

The EKF-SLAM approach employs a joint state vector, encapsulating both robot and landmark information.

Vector Definition

$$\mu = [x, y, \theta, x_1, y_1, \ldots, x_5, y_5]^T$$

Holistic Estimation

This vector collectively estimates the robot's pose (x, y,θ) and the positions of all five landmarks (xi, yi).

Correlation Maintenance

Crucially, this joint representation naturally maintains the statistical correlation between the robot's estimated pose and the mapped environment.

EKF Prediction: Motion Model

Nonlinear Motion

The prediction phase leverages a non-linear differential-drive motion model to forecast the robot's next state.

State Prediction

$$\bar{\mu}_t = g(\mu_{t-1}, u_t)$$

This equation describes the predicted mean $\bar{\mu}_t$ state based on the previous state μ_{t-1} and control input u_t

Covariance Prediction

$$\bar{\Sigma}_t = G_t \Sigma_{t-1} G_t^T + R_t$$

The predicted covariance accounts for uncertainty propagation, where *G_t* is the Jacobian of the motion model and *R_t* represents the process noise covariance.

Gaussian Motion Noise

Process noise, modelled as Gaussian, quantifies the inherent uncertainty in the robot's actuators and motion.

Measurement & EKF Update

Camera Measurements

The camera provides critical range (r) and bearing (ϕ) measurements to detected landmarks.

Range Calculation

$$r = \sqrt{(x_i - x)^2 + (y_i - y)^2}$$

Calculated from the robot's current pose (x, y) and landmark position (xi, yi).

Bearing Calculation

$$\phi = \mathrm{atan2}(y_i - y, x_i - x) - \theta$$

This determines the angle of the landmark relative to the robot's heading .

Innovation

$$v_t = z_t - \hat{z}_t$$

The innovation term represents the discrepancy between the actual measurement z_t and the predicted measurement .

Kalman Gain

The Kalman Gain is used to optimally correct the predicted state and covariance based on these new measurements.

$$K_t^i = \bar{\Sigma}_t \, H_t^{iT} (H_t^i \, \bar{\Sigma}_t \, H_t^{iT} + Q_t)^{-1}$$

Landmark Initialization & Noise Tuning

New Landmark Initialization

When a new landmark is observed for the first time, its position is initialized in the global frame using the robot's current pose and the observed measurement.

$$x_i = x + r\cos(\theta + \phi)$$

$$y_i = y + r\sin(\theta + \phi)$$

Initial Uncertainty

Newly initialized landmarks are assigned a high initial covariance, reflecting the significant uncertainty in their initial estimated position.

Covariance Reduction

Subsequent observations of the same landmark gradually reduce its associated covariance, improving the accuracy of its estimated position.

Noise Parameter Tuning

Proper tuning of the process noise covariance (R) and measurement noise covariance (Q) is critical for maintaining EKF stability and consistency.

$$Q_t = \begin{pmatrix} \sigma_r^2 & 0 & 0 \\ 0 & \sigma_\phi^2 & 0 \\ 0 & 0 & \sigma_s^2 \end{pmatrix}.$$

$$R_t = \begin{bmatrix} \sigma_x^2 & 0 & 0 \\ 0 & \sigma_y^2 & 0 \\ 0 & 0 & \sigma_\theta^2 \end{bmatrix}$$

Jacobian matrices

Motion Jacobian

$$G_t = I + F_x^T \begin{pmatrix} 0 & 0 & -\frac{v_t}{\omega_t}\cos\mu_{t-1,\theta} + \frac{v_t}{\omega_t}\cos(\mu_{t-1,\theta} + \omega_t \Delta t) \\ 0 & 0 & -\frac{v_t}{\omega_t}\sin\mu_{t-1,\theta} + \frac{v_t}{\omega_t}\sin(\mu_{t-1,\theta} + \omega_t \Delta t) \\ 0 & 0 & 0 \end{pmatrix} F_x$$

Measurement Jacobian

$$H_t^i = \frac{1}{q} \begin{pmatrix} -\sqrt{q}\delta_x & -\sqrt{q}\delta_y & 0 & +\sqrt{q}\delta_x & \sqrt{q}\delta_y & 0 \\ \delta_y & -\delta_x & -q & -\delta_y & +\delta_x & 0 \\ 0 & 0 & 0 & 0 & 0 & q \end{pmatrix} F_{x,j}$$

EKF Flow Chart

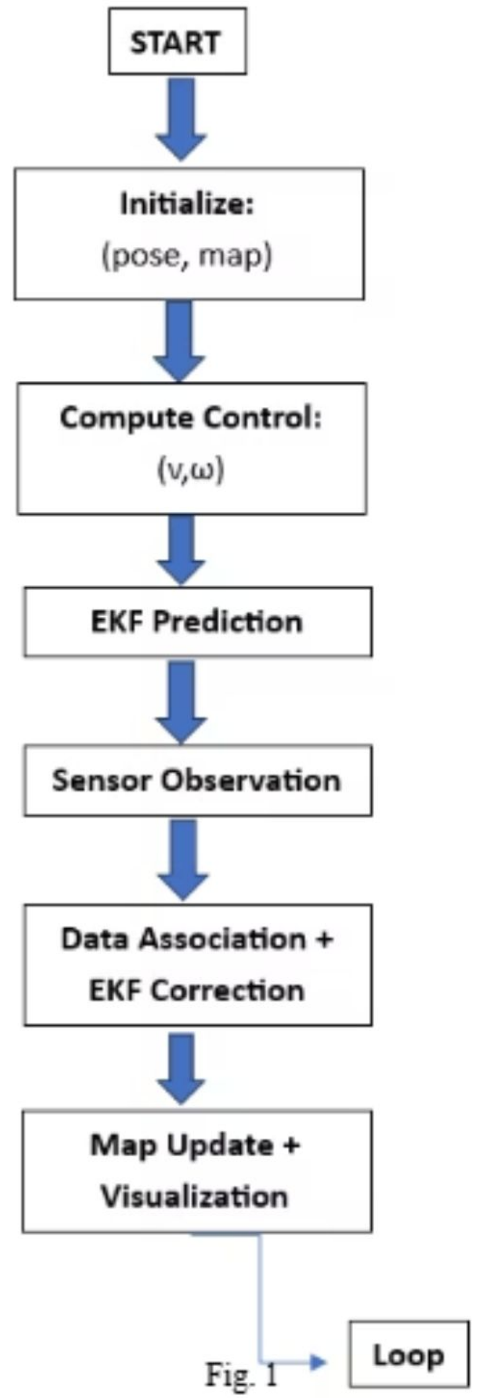


Fig. 1

Results & Performance Analysis

Successful Navigation

The robot successfully navigated all predefined waypoints within the simulated indoor environment.

Drift Correction

EKF-SLAM effectively corrected odometry drift, providing a significantly more accurate trajectory than odometry-only methods.

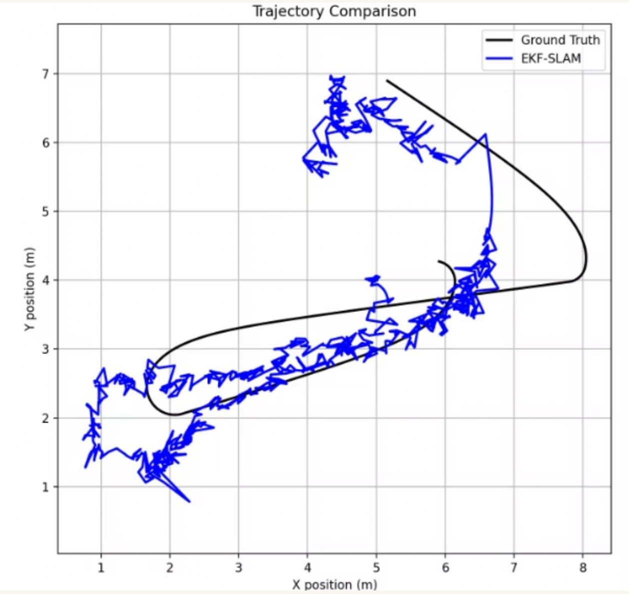
Landmark Convergence

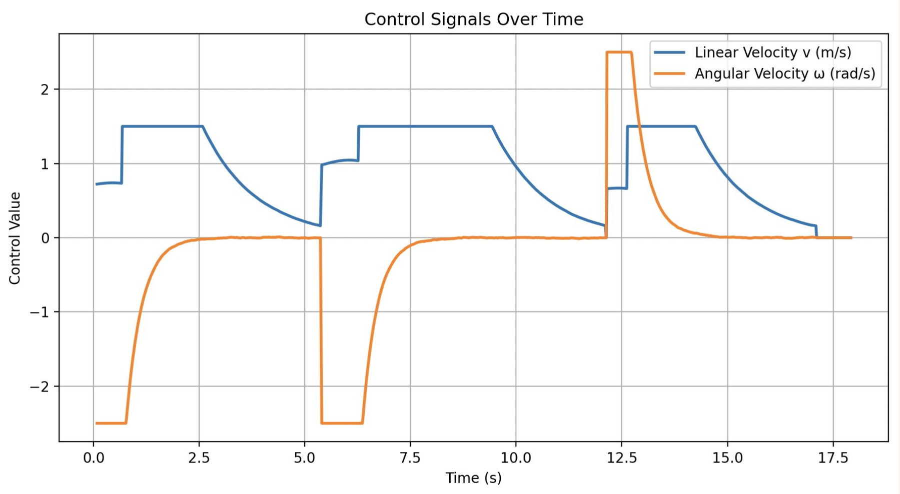
Uncertainties associated with landmark positions consistently converged to below 0.8m, demonstrating robust mapping.

Performance Comparison

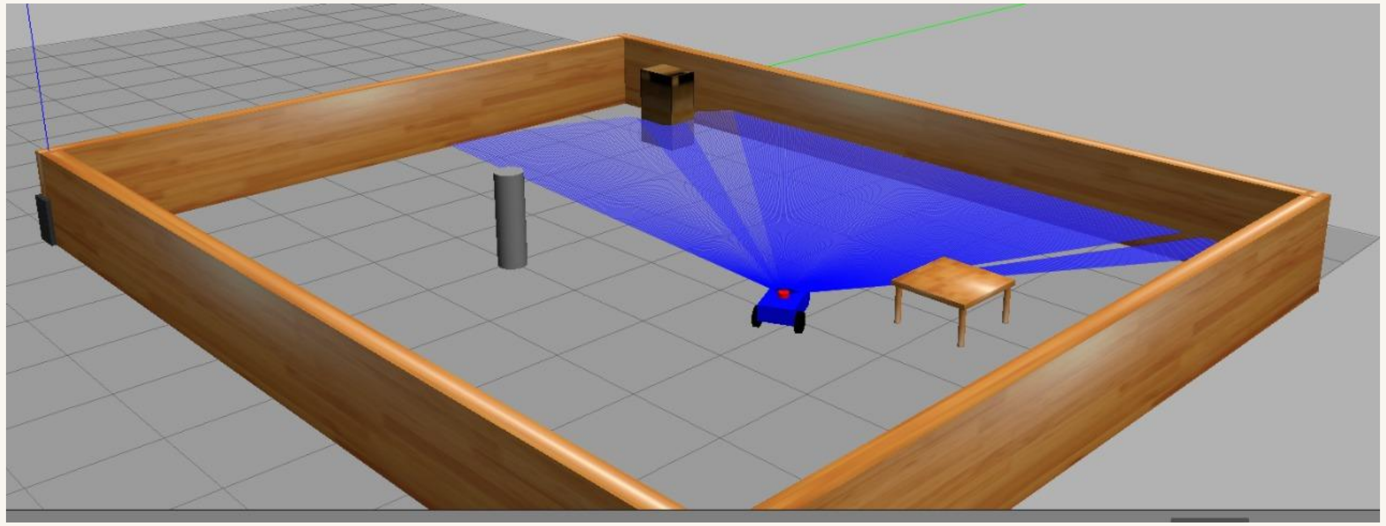
Odometry-only: Exhibited unbounded drift, rendering long-term navigation unreliable.

EKF-SLAM: Achieved a bounded and highly accurate trajectory, crucial for autonomous operation.



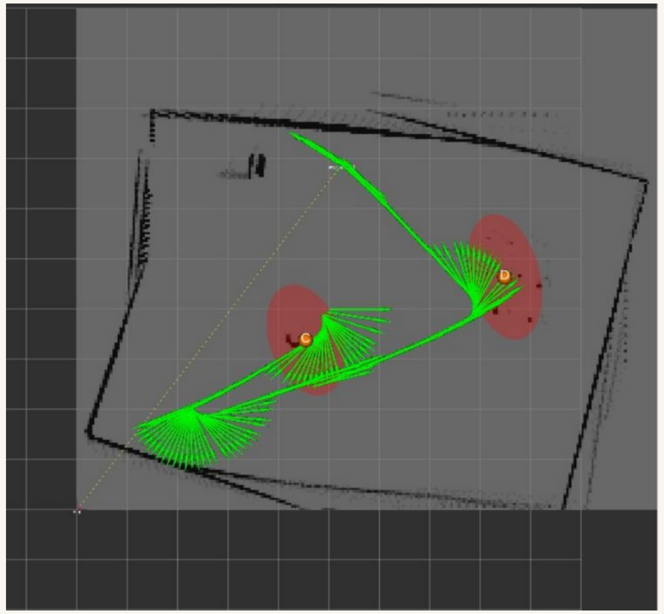


Implementation Results

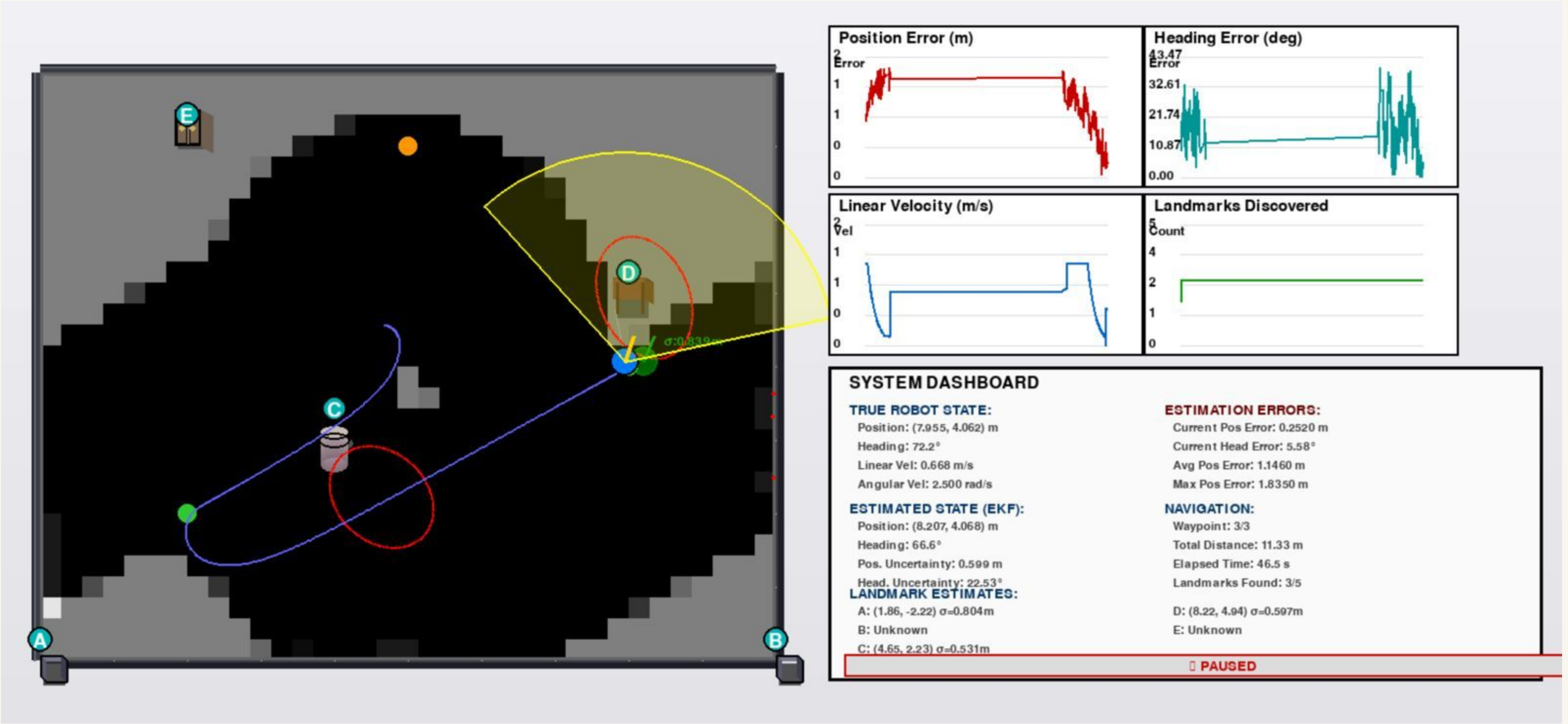


ROS Implementation

RViz Trajectory of robot



Pygame Implementation



Conclusion & Future Scope

Integrated Solution

EKF-SLAM successfully integrated robust motion modelling with probabilistic estimation for autonomous navigation.

Enhanced Accuracy

Demonstrated significant uncertainty reduction and maintained consistent state estimates over time.

Future Work: Visual SLAM

Exploring visual feature-based SLAM for richer environmental understanding and robustness.

Future Work: Real-World Deployment

Transitioning to ROS and deploying the solution on a physical robot for practical validation.

Future Work: Advanced Methods

Investigating 3D SLAM and graph-based optimisation techniques for more complex environments.