

HW1: State Estimation in 2D using ROS2

RAS 598: Space Robotics and AI

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Problem Description

The objective of this assignment is to perform 2D state estimation using ROS2 and to evaluate the performance of a PD controller in a simulated environment. The assignment involves tuning the proportional and derivative gains to minimize the cross-track error while following a boustrophedon path. Additionally, the effect of the spacing parameter on coverage is analyzed.



Figure 1: Path that has to be optimized by tweaking PD gains and spacing

The above image corresponds to the following parameters:

- `Kp_linear`: 10.0
- `Kd_linear`: 0.1
- `Kp_angular`: 5.0
- `Kd_angular`: 0.2
- `spacing`: 1.0

Methodology

Real-Time Tuning with RQT

- Used `rqt_plot` to visualize performance metrics such as cross-track error.
- Utilized `rqt_configure` to modify the PD gains and observe their effect in real-time.
- Observations:
 - Tweaking `Kp_linear`:
 - * Increasing `Kp_linear` results in faster convergence to the desired trajectory but can lead to overshooting and oscillations if too high.
 - * Decreasing `Kp_linear` results in slower convergence and a less responsive system.
 - Tweaking `Kd_linear`:
 - * Increasing `Kd_linear` helps dampen oscillations and stabilize the response but can slow down trajectory corrections.
 - * Decreasing `Kd_linear` reduces stability and can result in oscillatory behavior.
 - Tweaking `Kp_angular`:
 - * Increasing `Kp_angular` improves the system's ability to quickly correct angular errors but may cause sharp, abrupt movements if too high.
 - * Decreasing `Kp_angular` leads to slower angular error corrections and a less responsive trajectory.
 - Tweaking `Kd_angular`:
 - * Increasing `Kd_angular` stabilizes the angular response but may slow down corrections.
 - * Decreasing `Kd_angular` can lead to jerky angular adjustments and instability.
 - Adjusting `spacing`:
 - * Smaller spacing results in better path coverage but increases the computational load and requires tighter control to avoid overshooting.
 - * Larger spacing reduces computational load and trajectory adjustments but leads to gaps in coverage.
- Example Case:
 - With the following parameters:
 - * `Kp_linear = 2.0`, `Kd_linear = 0.1`
 - * `Kp_angular = 3.0`, `Kd_angular = 0.8`
 - * `spacing = 2.0`
 - The trajectory exhibited overcorrection, where the system oscillated excessively while attempting to correct its path.

- Plotted and observed the system's performance in the following figures:

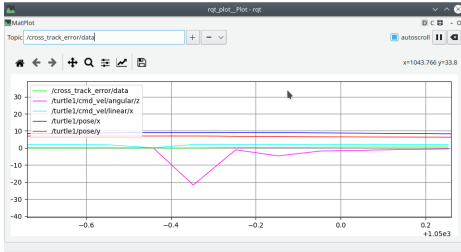


Figure 2: RQT Plot of Cross-Track Error

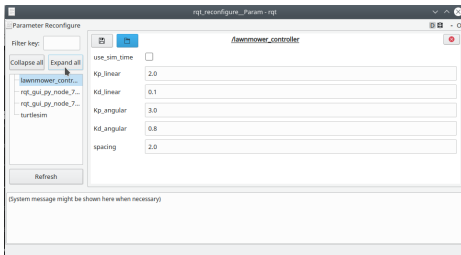


Figure 3: RQT Reconfigure Tool for Tuning Gains



Figure 4: Resulting Trajectory in Turtlesim

Bayesian Optimization

Bayesian Optimization is a powerful tool for optimizing functions that are expensive to evaluate. It uses a probabilistic model, typically a Gaussian Process, to estimate the objective function and iteratively selects parameters that are likely to minimize (or maximize) the objective.

- Why it is useful here:
 - Optimizing PD gains manually can be time-consuming and non-intuitive, especially when multiple parameters interact in complex ways.
 - Bayesian Optimization efficiently searches the parameter space to find a near-optimal solution with fewer evaluations compared to grid or random search.
- Application in this assignment:
 - Used Bayesian Optimization to minimize the cross-track error by systematically tuning the K_p and K_d parameters for both linear and angular controllers.
 - The optimizer focuses on high-value regions in the parameter space, ensuring better performance while reducing manual effort.

Implementation

Optimizer Code

- A new file, `boustrophedon_optimizer.py`, was created to optimize the PD gains for a specific spacing value.
- The optimization minimizes cross-track error using Bayesian Optimization from the `optuna` library. The process involves fixing the `spacing` parameter and tuning the PD gains (`Kp_linear`, `Kd_linear`, `Kp_angular`, and `Kd_angular`) for a given trajectory.
- To determine the optimal spacing, multiple optimizations are performed for different `spacing` values. This ensures the best balance between coverage and minimal cross-track error while ensuring the PD gains are appropriate for each spacing.
- The best parameters for each optimization run are saved in a text file for future reference. The following code snippet explains the key components of the optimization process:

Python Code

```
1 import optuna
2
3 class BoustrophedonOptimizer(Node):
4     def optimize_gains(self):
5         def objective(trial):
6             # Suggest PD gains for optimization
7             Kp_linear = trial.suggest_float('Kp_linear', *self.KP_LINEAR_RANGE)
8             Kd_linear = trial.suggest_float('Kd_linear', *self.KD_LINEAR_RANGE)
9             Kp_angular = trial.suggest_float('Kp_angular', *self.KP_ANGULAR_RANGE)
10            Kd_angular = trial.suggest_float('Kd_angular', *self.KD_ANGULAR_RANGE)
11
12            # Simulate controller and compute average cross-track error
13            avg_error = self.simulate_controller(Kp_linear, Kd_linear, Kp_angular,
14            Kd_angular)
15            return avg_error
16
17            # Fix the spacing for this optimization
18            self.spacing = 0.5 # Example spacing
19            self.get_logger().info(f"Running optimization for spacing={self.spacing}")
20
21            # Run Bayesian Optimization with optuna
22            study = optuna.create_study(direction="minimize")
23            study.optimize(objective, n_trials=self.n_trials)
24
25            # Save the best parameters
26            best_params = study.best_params
27            best_value = study.best_value
28            self.get_logger().info(f"Best parameters: {best_params}")
29            self.get_logger().info(f"Best average cross-track error: {best_value:.3f}")
30
31            # Save results to a text file
32            with open('best_params.txt', 'w') as f:
33                f.write(f"Best parameters: {best_params}\n")
34                f.write(f"Best average cross-track error: {best_value:.3f}\n")
35
36            return best_params
```

Listing 1: Optimizer Code Snippet

- The `objective` function defines the optimization target, minimizing the average cross-track error by systematically tuning the PD gains.

- The `spacing` parameter is kept constant during each optimization run, as seen in `self.spacing = 0.5`. To find the best spacing value, multiple optimizations are performed by updating `self.spacing`.
- Once the optimization is complete:
 - The best PD gains and their corresponding cross-track error are logged.
 - The best parameters are saved in a text file (`best_params.txt`) for future use.

Workflow

1. Run the optimizer to determine the best parameters using Bayesian Optimization.
2. Save the best parameters and their corresponding cross-track error in a text file for future reference.
3. Output from the `boustrophedon_optimizer` is shown below:

- Output:

```

1 [INFO] [1737972824.622087790] [boustrophedon_optimizer]:
2 Best parameters found: {'Kp_linear': 5.0014964543025275,
3 'Kd_linear': 0.3440134687670172,
4 'Kp_angular': 9.299200927443698,
5 'Kd_angular': 0.10005046439984644}
6 [INFO] [1737972824.622312004] [boustrophedon_optimizer]:
7 Best average cross-track error: 0.205
8
```

Listing 2: Optimizer Output

4. The best parameters are then applied to the controller, and the final average cross-track error is calculated.

Results

- Output from `boustrophedon_controller.py`:

```

1 [boustrophedon_controller-2] [INFO] [1738046772.783766592] [lawnmower_controller
2 ]:
3 Cross-track error - Current: -0.003, Avg: 0.088, Min: 0.000, Max: 0.195, Segment
4 : (2.0,3.0)->(9.0,3.0)
5 [boustrophedon_controller-2] [INFO] [1738046772.785660082] [lawnmower_controller
6 ]:
7 Reached waypoint 22
8 [boustrophedon_controller-2] [INFO] [1738046772.883342999] [lawnmower_controller
9 ]:
10 Lawnmower pattern complete
11 [boustrophedon_controller-2] [INFO] [1738046772.885677395] [lawnmower_controller
12 ]:
13 Final average cross-track error: 0.088
14
```

Listing 3: Controller Output

- Final Gains and Spacing selected which yields a final average cross track error of 0.088.
 - Kp_linear: 5.0015
 - Kd_linear: 0.3440
 - Kp_angular: 9.2992
 - Kd_angular: 0.1000
 - Spacing: 0.5
- Image of the resulting trajectory:

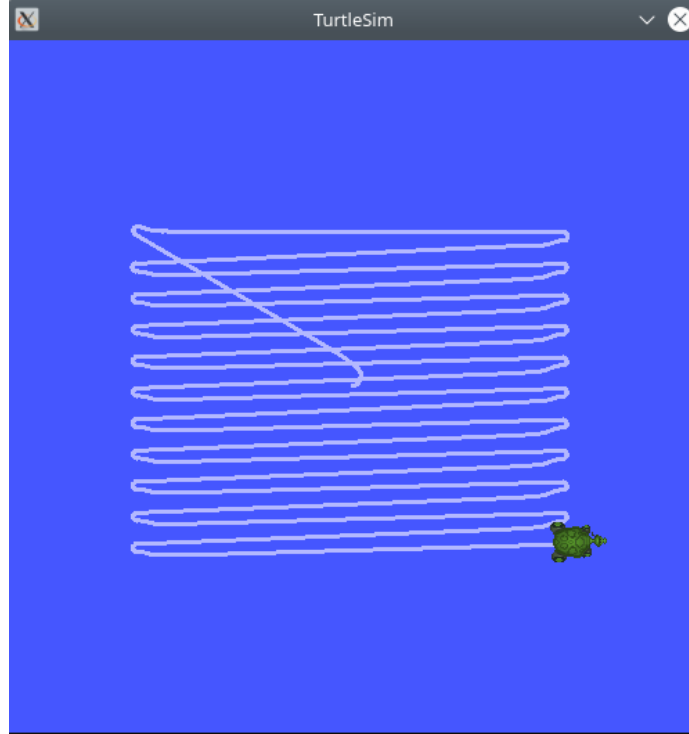


Figure 5: Resulting Trajectory with Optimized PD Gains and Spacing

- Comparison Between Optimizer and Controller Outputs:
 - The optimizer suggested a set of parameters that minimized the simulated average cross-track error to approximately 0.205.
 - When these parameters were applied in the actual controller, the final average cross-track error was measured as 0.088.
 - The improvement in the controller's performance compared to the optimizer's simulation may be attributed to real-time adjustments and better handling of dynamic factors by the controller.

- Reasoning for Spacing Selection:
 - Comparison of different spacing values:

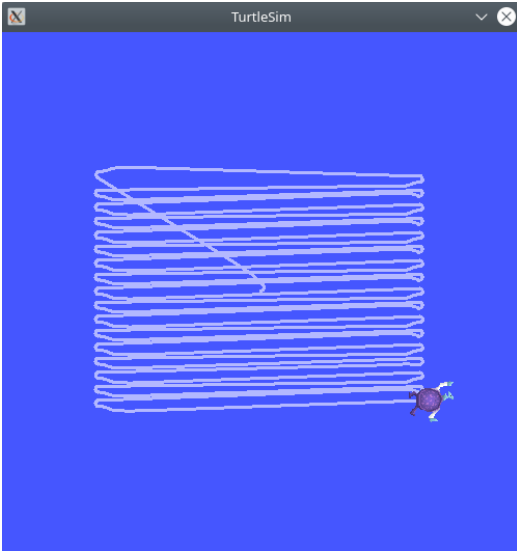


Figure 6: Spacing = 0.3

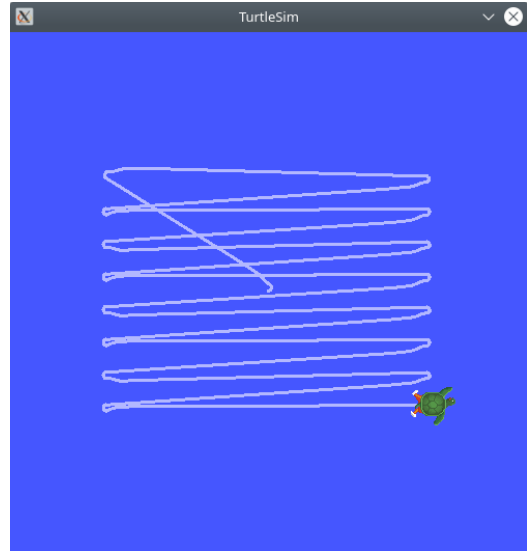


Figure 7: Spacing = 0.7

- The spacing value was kept constant during each optimization. However, for different spacing values, the PD controllers had to be re-optimized.
- After testing multiple spacing values and optimizing the gains for each, a spacing value of 0.5 was selected.
- At `spacing = 0.5`, the paths were:
 - Not too close, avoiding overlap and unnecessary corrections.
 - Not too far apart, ensuring adequate coverage without gaps in the lawnmower pattern.

Performance Plots

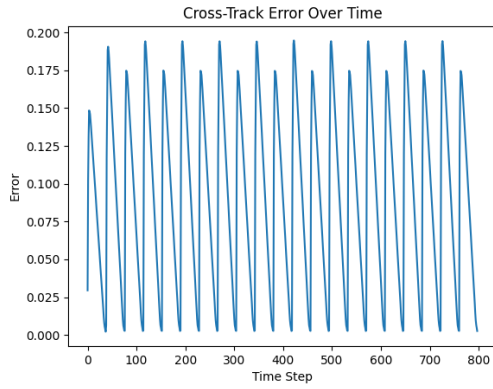


Figure 8: Cross-Track Error Over Time

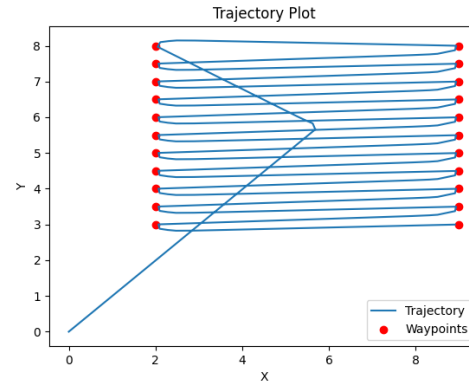


Figure 9: Trajectory Plot

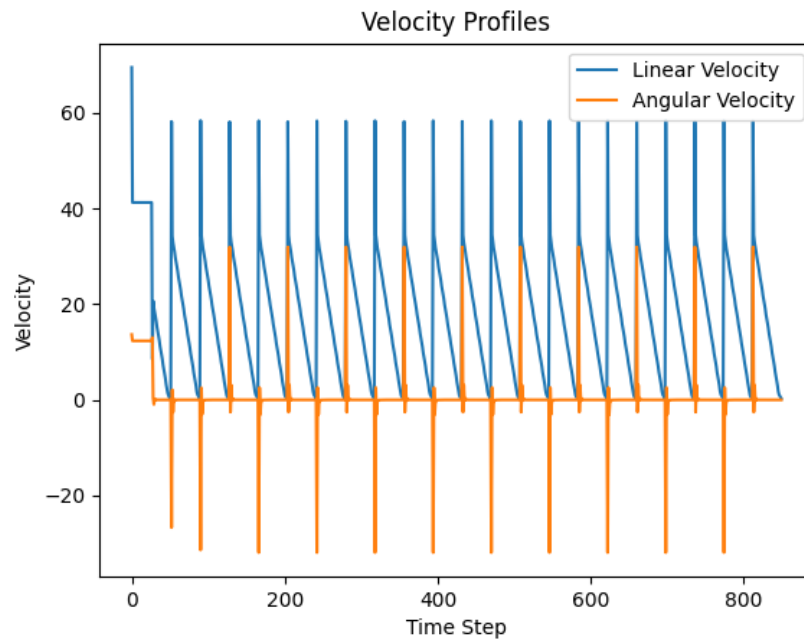


Figure 10: Velocity Profiles (Linear and Angular)

Challenges and Observations

- **Difficulties in Tuning Gains Manually:**
 - Small changes in K_p values led to large variations, making manual tuning difficult.
- **Impact of Spacing on Coverage:**
 - Small spacing (0.3) caused overlapping paths, while large spacing (0.7) left coverage gaps.
 - Spacing = 0.5 was optimal, balancing coverage without redundancy.
 - PD gains needed re-optimization for each spacing value.
- **Effectiveness of Bayesian Optimization:**
 - Automated tuning found optimal gains, reducing manual effort.
 - Optimized simulation error: 0.205; real controller error improved to 0.088.
 - Best gains were saved for reuse, improving efficiency.
- **Stability vs. Responsiveness Trade-off:**
 - High K_p improved response but increased oscillations.
 - Higher K_d reduced overshooting but slowed corrections.
 - Final selected gains balanced precision and stability.
- **Insights from Plots:**
 - Cross-Track Error Plot showed periodic oscillations.
 - Trajectory Plot revealed improved path following.
 - Velocity Profiles indicated rapid corrections due to PD control.