Modeling and Control for Vision Based Rear Wheel Drive Robot And Solving Indoor SLAM Problem using LIDAR

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Outline

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- Problem Statement & Contributions
- Hardware: Low Cost Self-Designed Robotic Vehicle
- Modeling & Control of Rear-Wheel Drive Robot
- Perform SLAM (Simultaneous localization and mapping)
- Demonstrations
- Summary and Directions for Future Research

Literature Survey: State of Field Use

1. Rear wheel drive robot TITO LTI model (Marino, et.al. 2007) – basis for both decoupled longitudinal and lateral plant

2. Vision based complete lateral model of RWD vehicle (Jana Kosecka, 1996) – vision based lateral dynamics and vision based outer loop design

3. Image processing algorithm in opencv2 (Bradski G, Kaehler A, 2008) – camera used to get directional information(8HZ, 320×240) or a USB camera (4.5Hz, 640×480)

4. ROS architecture and API (Morgan, et al. 2009) – basic introduction of the open source robot operation system I was using (ROS, Robot Operation System)

5. Hector Mapping, SLAM relies only on LIDAR scan data (Giorgio, et al. 2005) – EKF, Main algorithm implemented

6. Gmapping, SLAM relies on both odometry (encoder and IMU) and LIDAR scan data (SLAM for Dummies, Soren, et al.) – Extended Kalman Filter (EKF) is used to estimate the state of the robot from odometry data and landmark observation

Contributions

- General *FAME* architecture
- Self designed rear wheel drive multi-capability ground vehicle
- Modeling and control trade studies
- Inner loop $(v\ ,\omega)$ control
- Speed-directional outer loop (v, θ) control
- Planar $(x,\ y)$ Cartesian Stabilization
- Vision based outer loop (v, θ) control
- Line tracking performance study with:

  (1) Different cruise speed v_x

  (2) Different camera fixed look-ahead distance L

  (3) Different delay from vision subsystem T_d
- Manually remote controlled robot to perform indoor SLAM
- Autonomously line guided robot to perform indoor SLAM.

Motivation

Sensing / Monitoring

Foundations of Communications

Cooperative Planning & Control

Robots in the Market

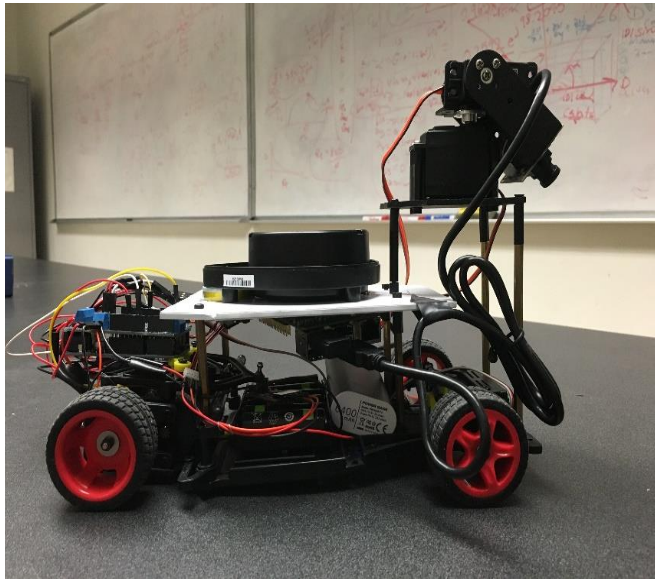
Pioneer 3 DX

- mapping
- teleoperation
- localization
- monitoring
- reconnaissance
- vision
- manipulation
- autonomous navigation
- multi-robot cooperation and other behaviors
- general robotics

$ 4000 **Pioneer 3 DX**

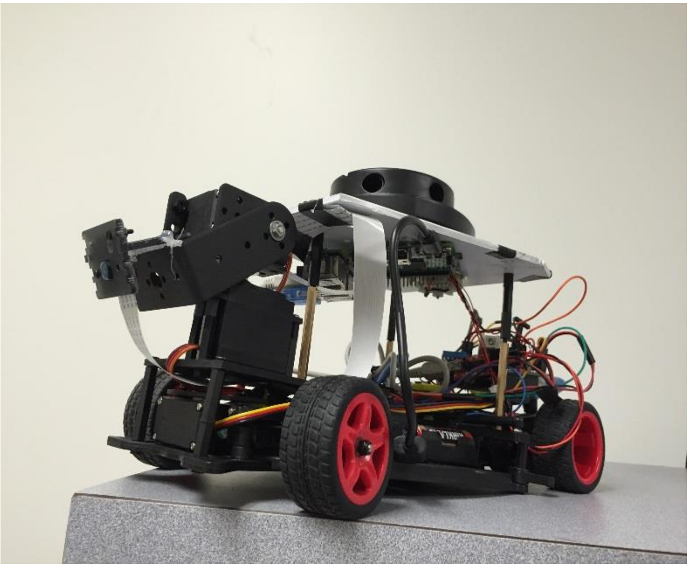
Powerful but Expensive

Robots (Different Styles and Modes)



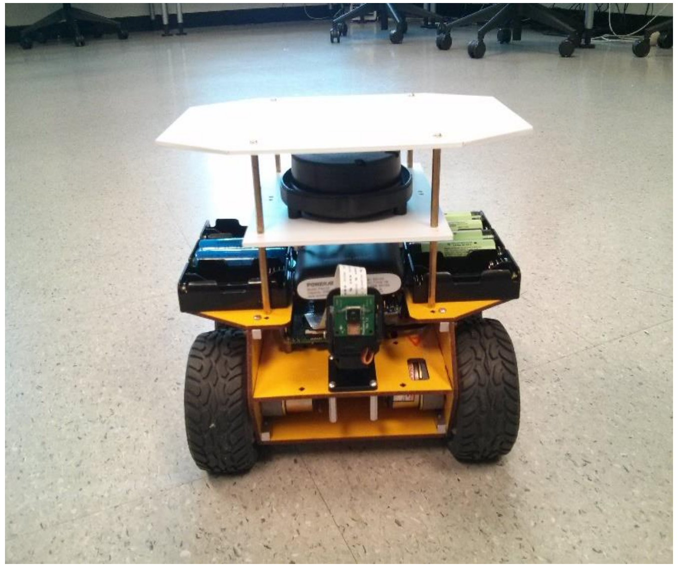
FreeSLAM Robot: Vision Mode

Rear Wheel Drive, UAV Tracking, Camera vision sensing, Depth sensors



FreeSLAM Robot: LIDAR Mode

High Accuracy LIDAR Sensing, Fixed Pan Servo, Less Speed for not Losing Landmarks

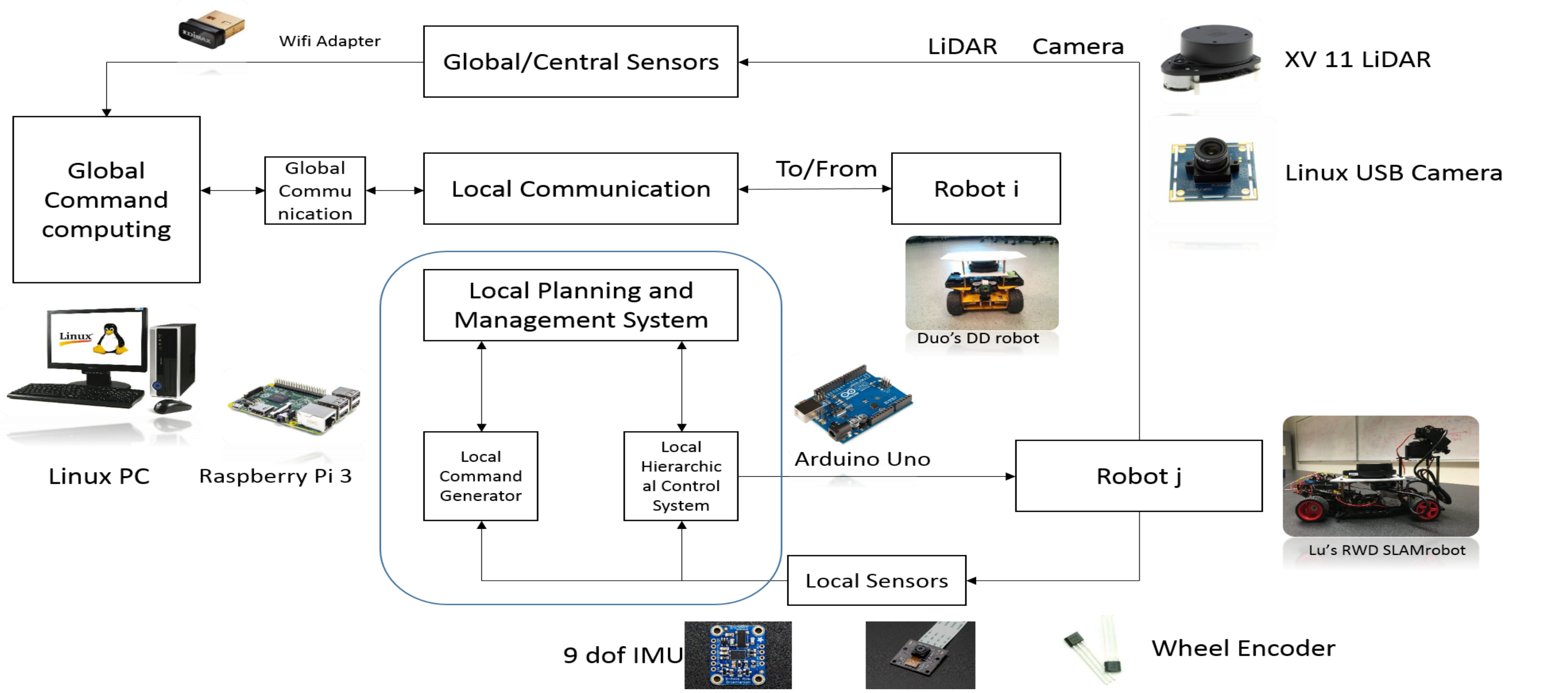


Duo Lv's Robot: Rigid Mode

Differential Drive, UAV landing, Less Speed, More Rigid, Easy Turning

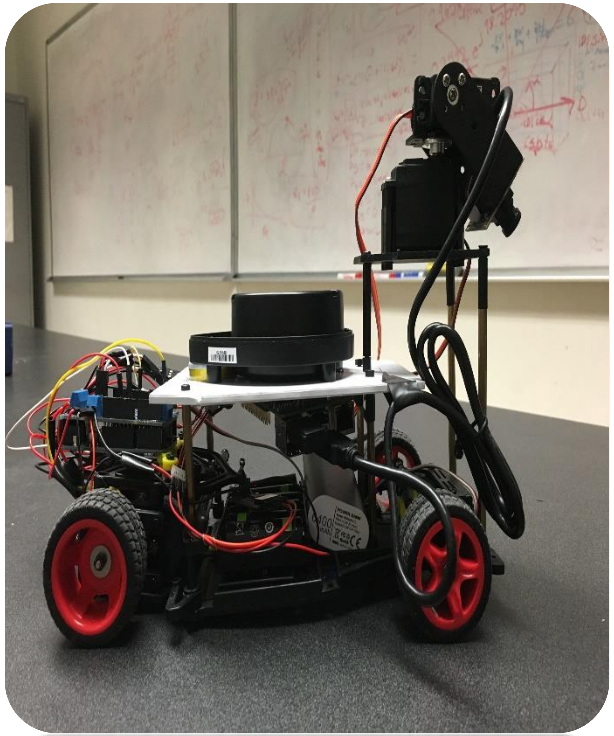
FAME Architecture

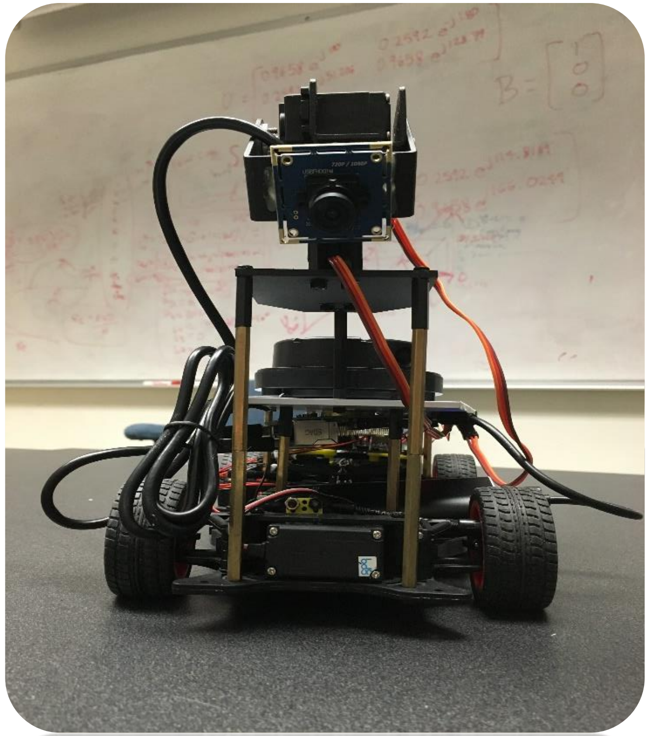
- *Flexible Autonomous Machines operating in an uncertain Environment*
- Candidate system-level architecture for a fleet of robotic vehicles



Hardware

Enhanced FreeSLAM Robot





Component	Price
Chassis and Motors	$180
Futaba S3003 Servo	$10
Arduino Uno	$25
Adafruit Motor Shield	$20
Raspberry Pi 3	$40
WiFi adapter	$25
Adafruit 9DOF IMU	$20
Pi camera	$20
Neato xv11 LIDAR	$80
5V external battery for Raspberry Pi	$20
Hitachi 18650 battery for motor	$30
Total Price	**$470**

Robot Nominal Parameter Values and Characteristics

Table 1.2: FreeSLAM Robot Nominal Parameter Values and Characteristics

Parameters	Definition	Nominal Values
m	Fully Loaded Mass	1.47kg
m_0	Mass (Not Loaded)	0.83kg
I	Moment of Inertia (Estimated using Cube)	0.0015kgm2
r	Wheel Radius	0.024m
d_w	Distance Btw 2 Rear Wheels	0.134m
L_a	Armature Inductance	0.2mH (neglected)
R_a	Armature Resistance	2.523Ω
K_b	Back EMF Constant	0.004V/(rad/sec)
K_t	Torque Constant	0.004Nm/A
v_{max}	Max. Observed Speed (Enhanced Vehicle)	5m/s
v_{max0}	Max. Observed Speed (Original vehicle)	7.2m/s
e_{amax}	Max. Motor Voltage	7.2V
a_{max}	Max. Accel. (Enhanced)	3.2m/sec2
$\omega_{wheelmax}$	Max. Angular Vel. (Enhanced)	208.3 rad/sec

Hardware Limitation

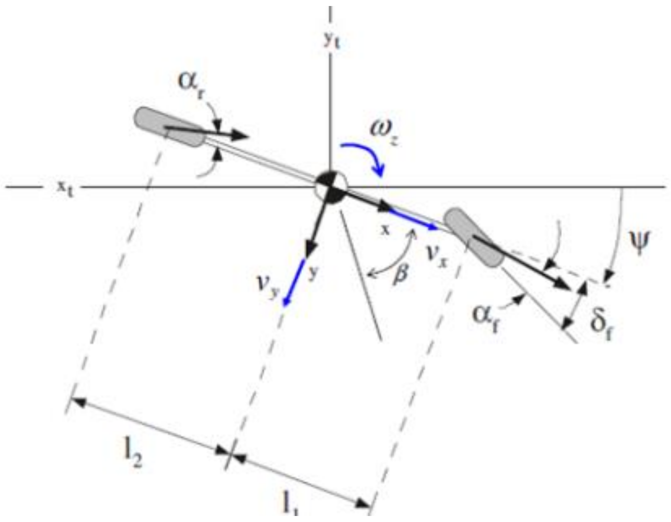
Sensors/Actuators/ Software	t (sec)	ω (rad/s)	Bandwidth Limitations (factor of 10 rule)
Arduino ZOH ½ sample delay	0.05	$\frac{2}{\Delta} = 40$	4 rad/s
Arduino DA/AD	0.1	60	6 rad/s
Image Processing	0.133	47.1	4.7 rad/s
Wheel Encoders	0.0131 v	479.4 v	4.79 v rad/s
BNO055 9 dof IMU	0.01	600	60 rad/s

Inner Loop Bandwidth is limited by 4 rad/s

Rear Wheel Drive Robot – State Space Representation
(Marino, et.al. 2007)

$$\begin{bmatrix} \dot{v}_x \\ \dot{v}_y \\ \dot{\psi} \\ \ddot{\psi} \end{bmatrix} = \begin{bmatrix} \frac{-2v_x c_a}{m} & 0 & 0 & 0 \\ 0 & -\frac{c_f+c_r}{mv_x} & 0 & -v_x + \frac{c_r l_r - c_f l_f}{mv_x} \\ 0 & 0 & 0 & 1 \\ 0 & \frac{-l_f c_f + l_r c_r}{I v_x} & 0 & -\frac{l_f^2 c_f + l_r^2 c_r}{I v_x} \end{bmatrix} \begin{bmatrix} v_x \\ v_y \\ \psi \\ \dot{\psi} \end{bmatrix} + \begin{bmatrix} \frac{1}{m} & 0 \\ 0 & \frac{c_f}{m} \\ 0 & 0 \\ 0 & \frac{l_f c_f}{I} \end{bmatrix} \begin{bmatrix} F \\ \delta_f \end{bmatrix} \quad y = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} v_x \\ v_y \\ \psi \\ \dot{\psi} \end{bmatrix}$$

Decoupled
TITO LTI System



$$P_{long} = \frac{V_x}{F} = \left[\frac{0.6803}{(s+1.116)}\right]$$

➢ (Analysis in next slide)

Equilibrium cruise speed of $v_e = 0.1m/s$:

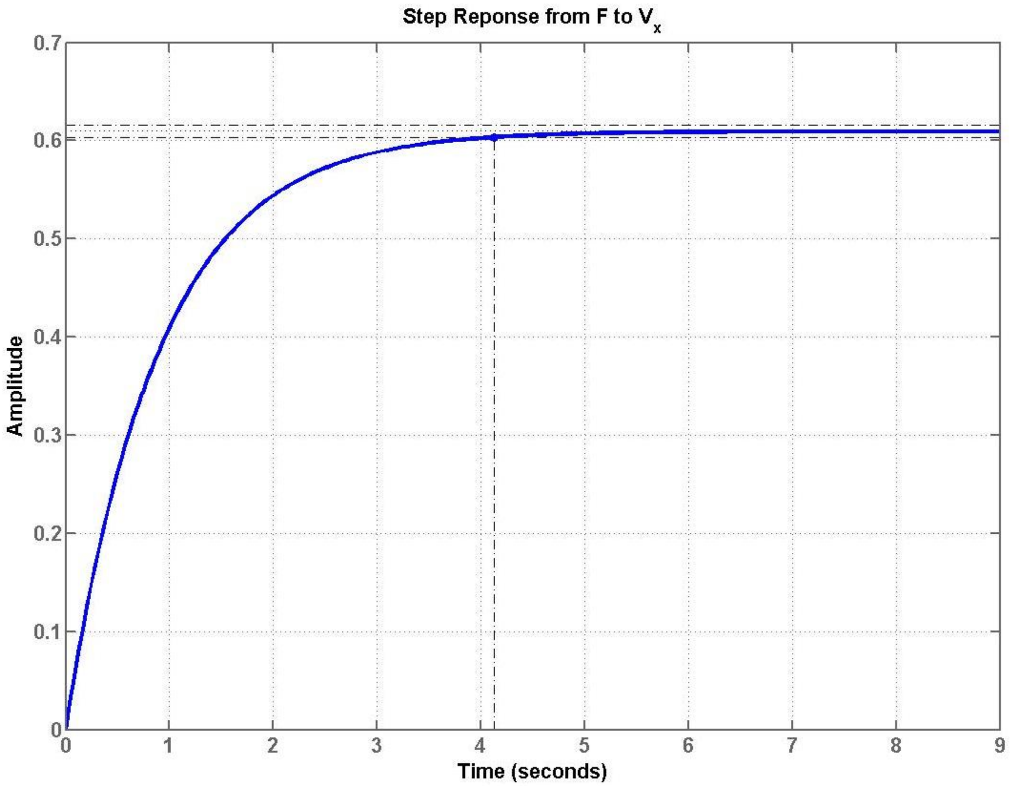
$$P_{Lateral} = \frac{\dot{\psi}}{\delta_f} = \frac{0.368(s+0.484)}{(s+1.007)(s+0.457)}$$

Why This Calculated Numerical Model is Not Quite Accurate

$$P_{long} = \frac{b}{s+a}$$

$$P_{long} = \frac{V_x}{F} = \left[\frac{0.6803}{(s+1.116)}\right]$$

- $t_s = \frac{5}{a}$ (1%)= 4.48s
- $\frac{y_{ss}}{e_{ss}} = \frac{b}{a} = \frac{0.6803}{1.116} = 0.61$



- a = 1.116
- b = 0.6803

$I = 0.0015 kg \cdot m^2$ (car is estimated as a cube)

$c_f = c_r = 0.0368\ N/rad$ (estimated wheel rotary stiffness)

Why model is not quite accurate:

- Inaccurate c_f, c_r and I
- Static friction

Robot Motor Parameter Estimations

DC Motor Transfer Function
(From input voltage to angular velocity)

$$\frac{\Omega(s)}{U_a(s)} = \frac{K_t}{L_a J s^2 + s(L_a B + R_a J) + K_e K_t + R_a B}$$

Known the DC motor model is RN 260-C

- $L_a = 0.2mH$ (Armature Inductance)
- R_a: Armature Resistance

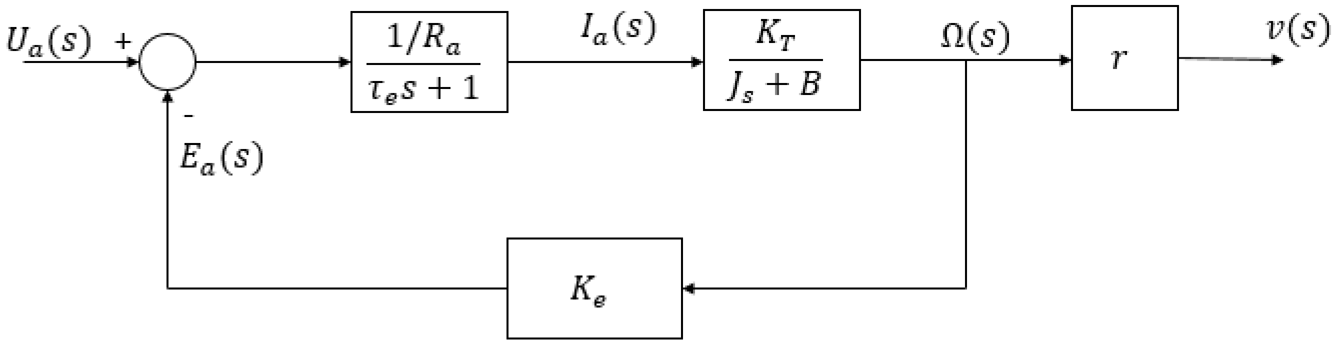
$$U_a = E_a + I_a R_a$$
$$P_1 = U_a I_a = 1.07\text{A} \times 4.5V = 4.815W$$
$$P_M = E_a I_a$$
$$R_a = \frac{P_1 - P_M}{{I_a}^2} = 2.523\Omega$$

Table 2.1: RN 260 Motor Dynamics

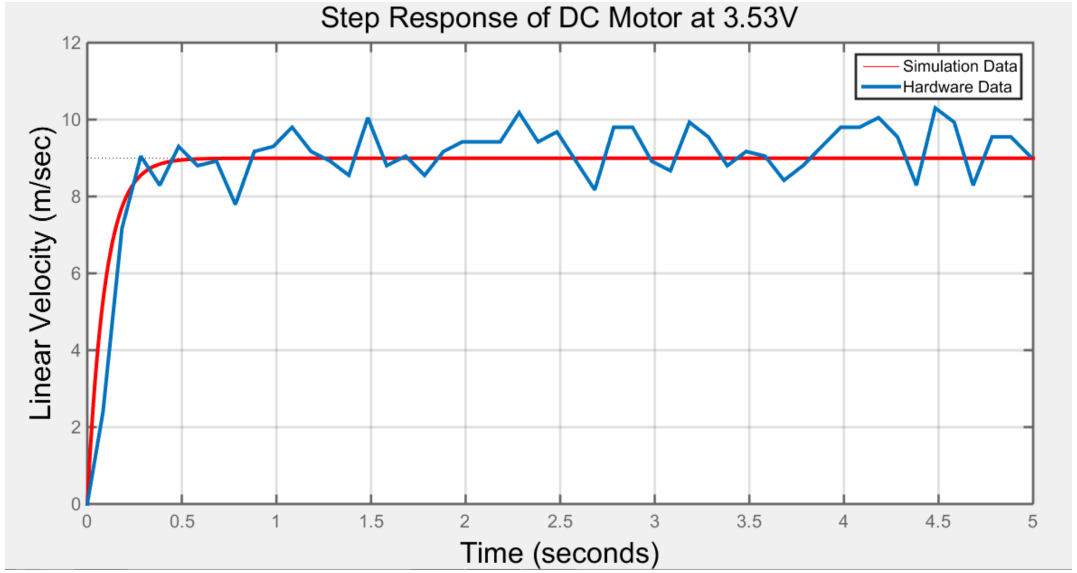
	Current (A)	Speed (rpm)	Torque (g*cm)	Voltage (V)
No Load	0.13	10000	0	4.5
Max Efficiency	0.51	7950	18	4.5
Max Output	1.07	5000	44	4.5
Stall	2	0	88	4.5

- K_t : motor torque constant
- K_e : motor back EMF constant
- J is moment of inertia of the motor shaft-load system
  $J = 2.96 \times 10^{-6}\ kg \cdot m^2$
- B is load-motor speed rotational damping constant
  $B = 4.3 \times 10^{-5}\ Nms$

DC Motor Dynamics



$$P_{motor} = \frac{v(s)}{e_a(s)} = \frac{27.1}{s + 10.64}$$

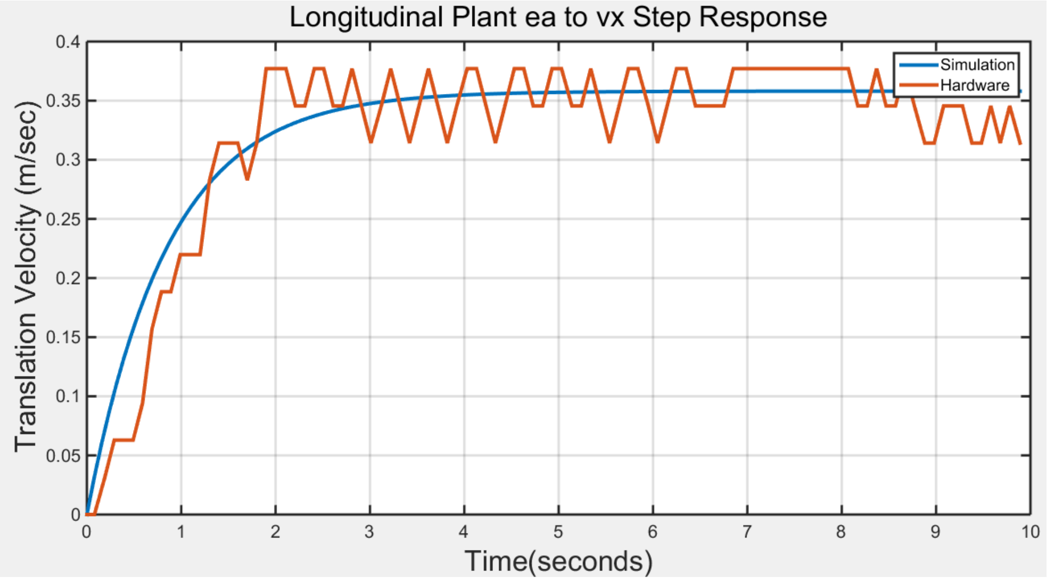


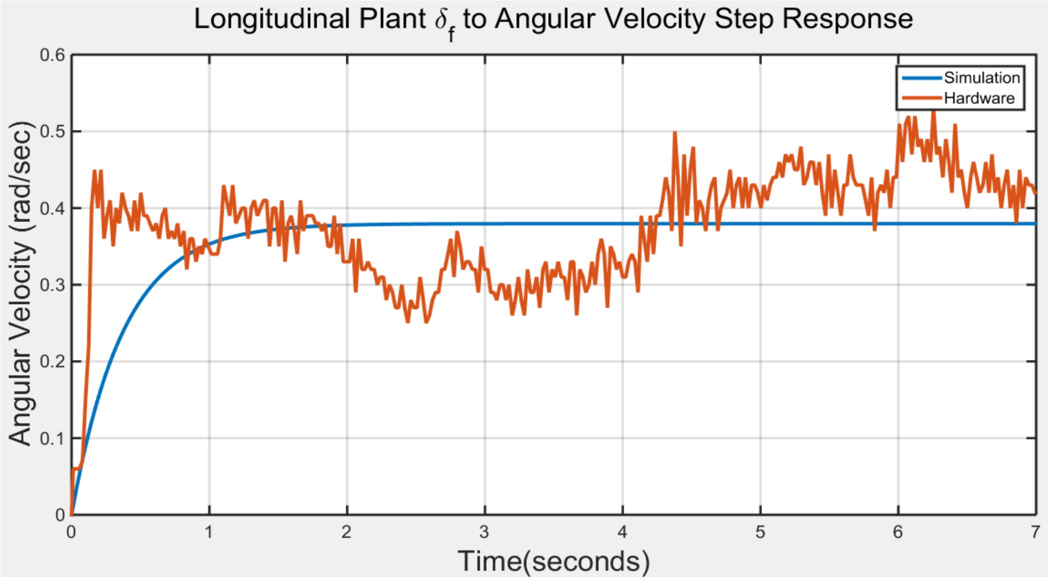
Step Response of DC Motor with

Motor input voltage is 3.53 V

- Step Response Ripple: 2.4 m/sec

On Ground Longitudinal and Lateral Model





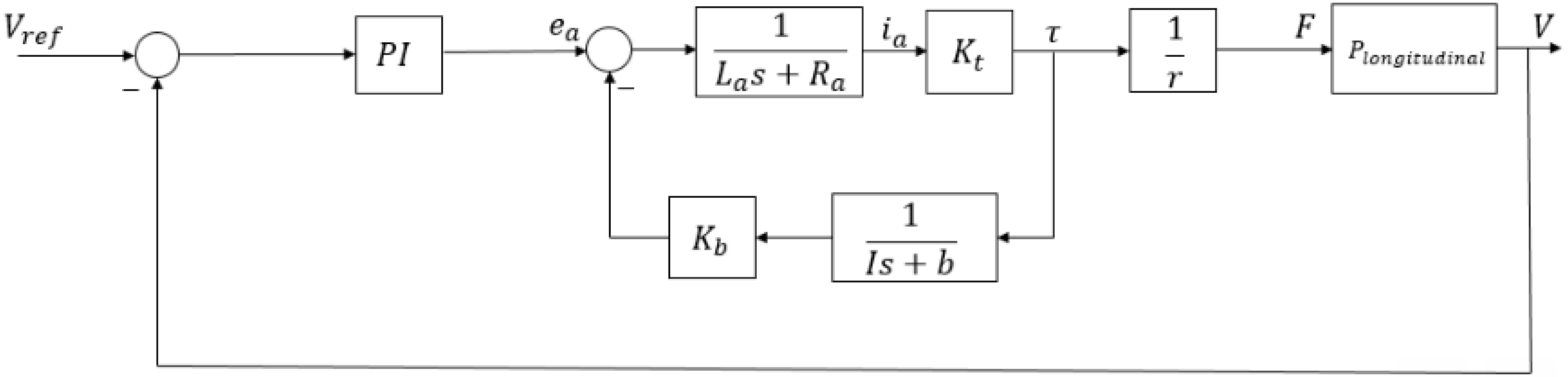
$$P_{long} = \frac{V_x}{e_a} = \frac{0.3274}{s + 1.176}$$

$$P_{lateral} = \frac{\dot{\psi}}{\delta_f} = \frac{2.892}{s + 2.659}$$

- Step Response Ripple: 0.06 m/sec
- Step Response Ripple: 0.27 rad/sec

Encoder is used to get linear velocity while IMU BON055 is used to get angular velocity information

Longitudinal Inner Loop PI Controller Design



PI controller: g = 11.68 z = 2.02

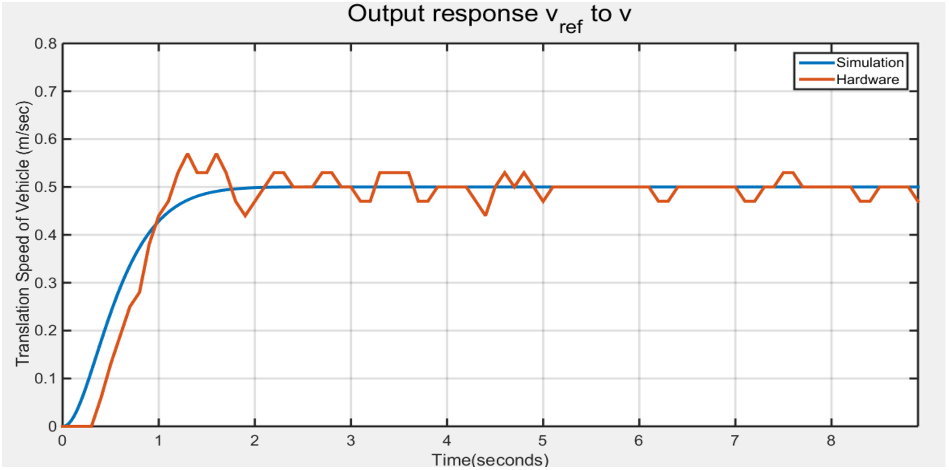
$$T_{ry} = WPK(1+PK)^{-1}$$

$$T_{ry} \xRightarrow{V_{ref}\ to\ V} \frac{7.716}{s^2+5s+7.716}$$

- Settling time t_s is set to 2 seconds
- Damping ratio ζ is set to 0.9

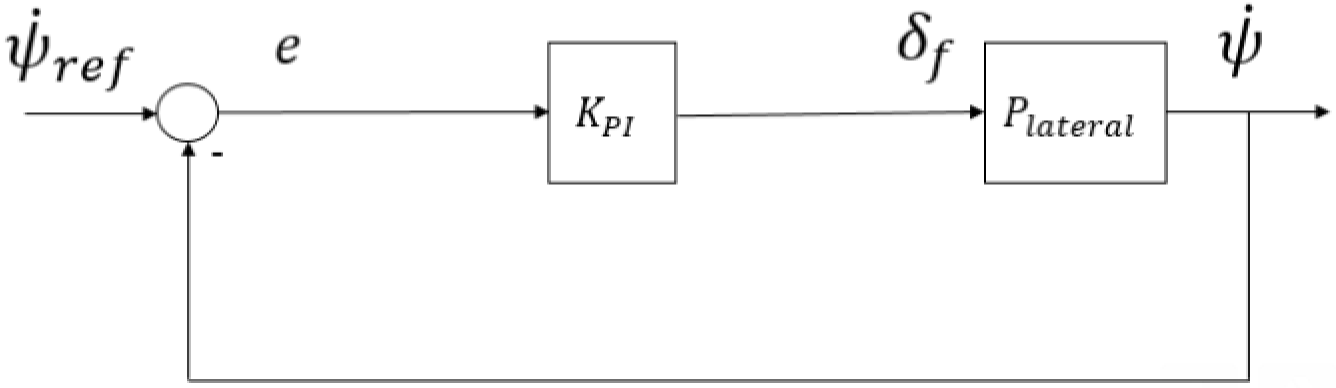
In this case

- ω_n is set to 2.78 rad/s
- Overshoot is 0.15%



Ripple: 0.06m/s

On Ground Lateral Inner Loop PI Controller Design



$\dot{\psi}_{ref}$ is desired angular velocity
δ_f is commanded front wheel steer angle

To design this PI controller

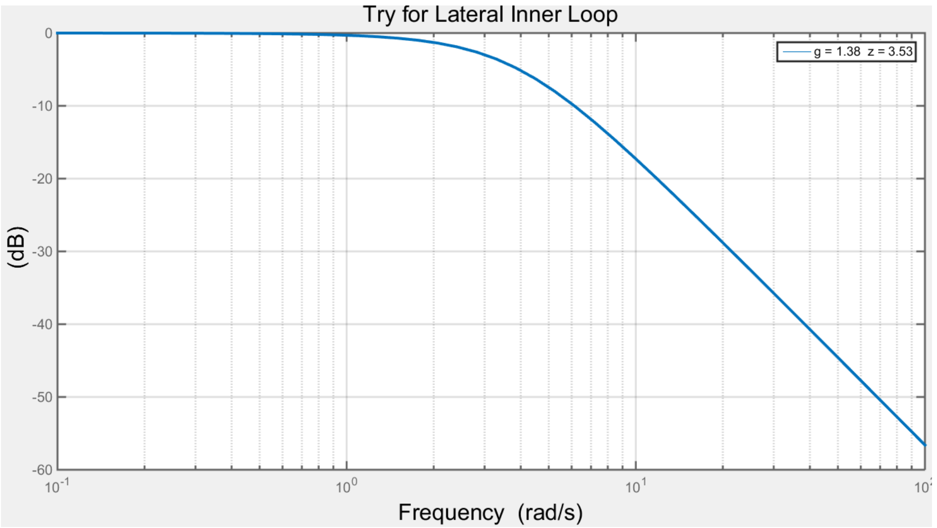
- Set settling time t_s to 1.5s
- Set damping ratio ζ to 0.886

In this case

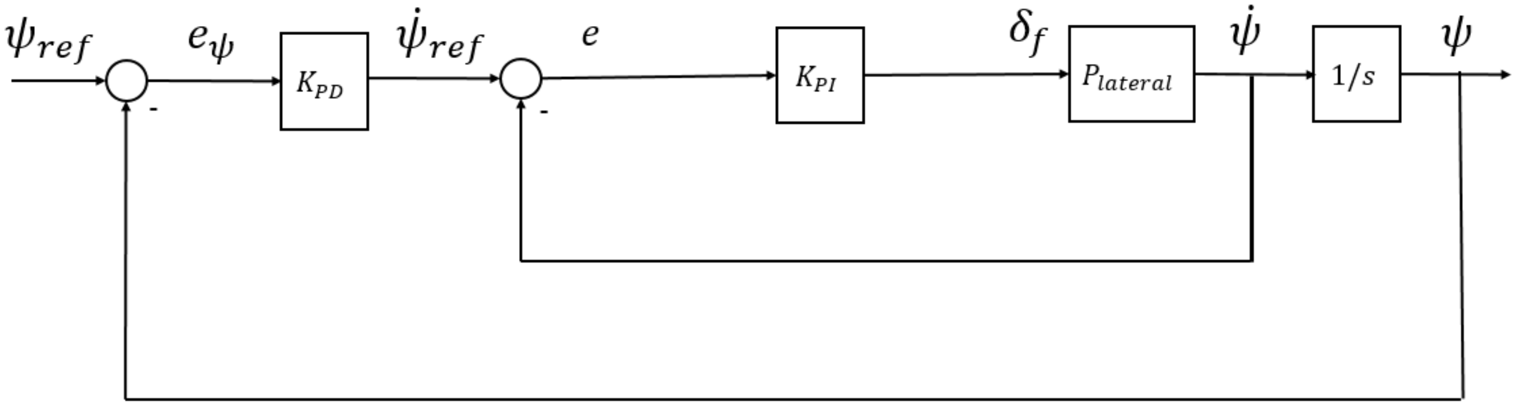
- ω_n is set to 3.8 rad/s
- Overshoot is set to 0.4%

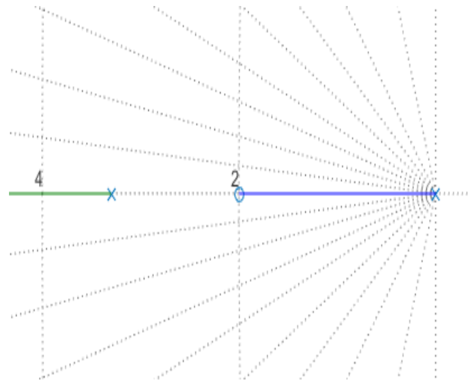
Then we have the PI controller: g = 1.38 z = 3.53

$$T_{ry} = WPK(1 + PK)^{-1} \qquad T_{ry} = \frac{14.8}{s^2 + 6.67s + 14.8}$$



Lateral Outer Loop PD Controller Design



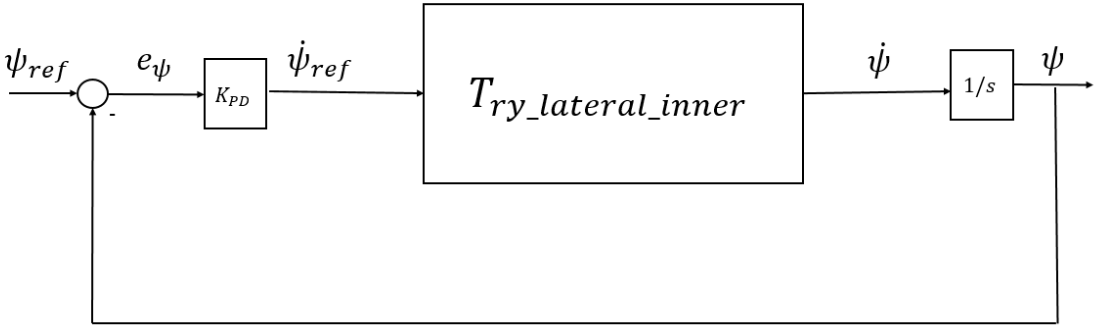


From system estimation aspect:

P_{outer} can be estimated as a

First order system with an integrator:

$$P_{outer} \approx \frac{3.3}{s(s+3.3)}$$



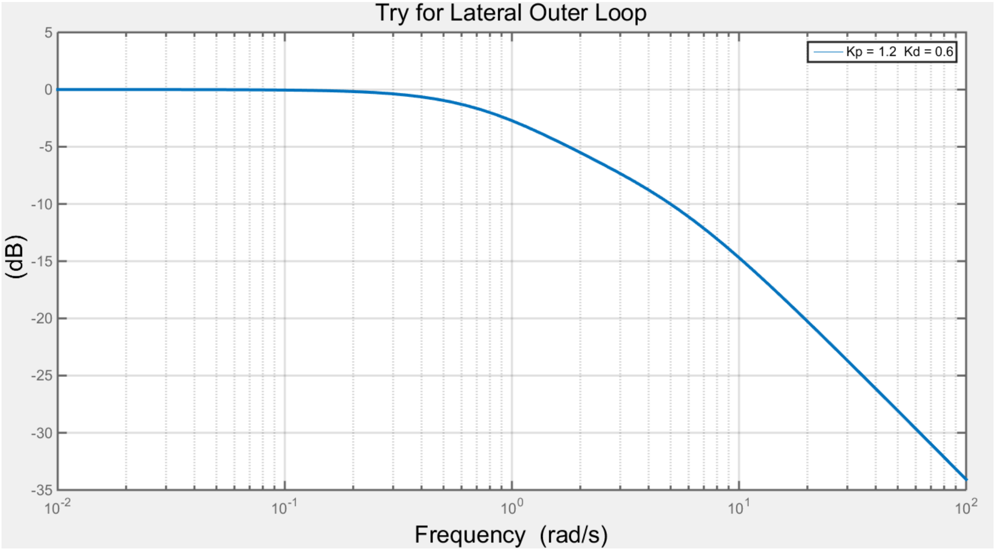
Using root locus method to design the PD controller:
(Put a zero at s = -2)

Kp = 1.2   Kd = 0.6   (g = 1.2 and z = 2)

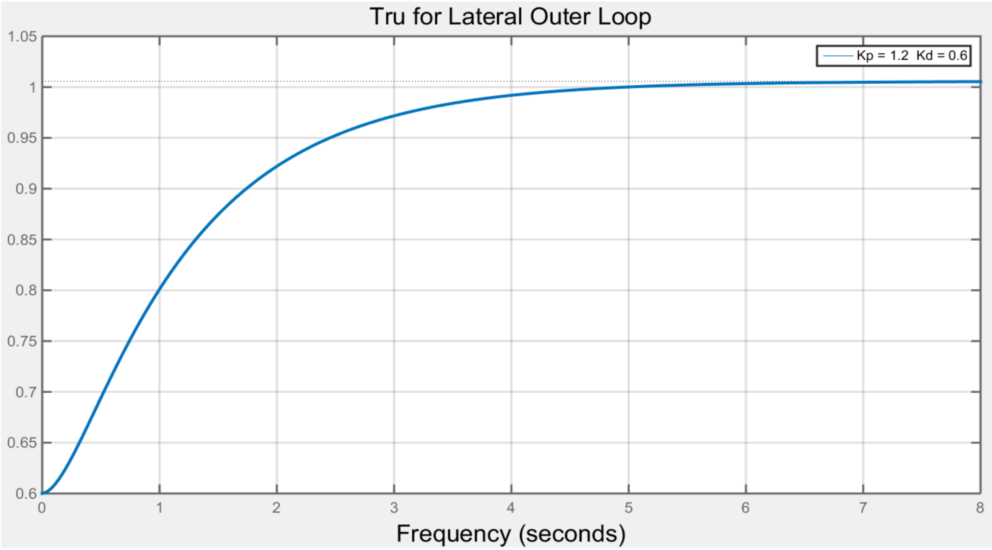
Lateral Outer Loop PD Controller Performance

$$T_{ry} = \frac{1.98(s+2)}{(s+0.9)(s+4.375)}$$

$$T_{ru} = \frac{0.6(s+3.3)(s+2)}{(s+0.9)(s+4.375)}$$

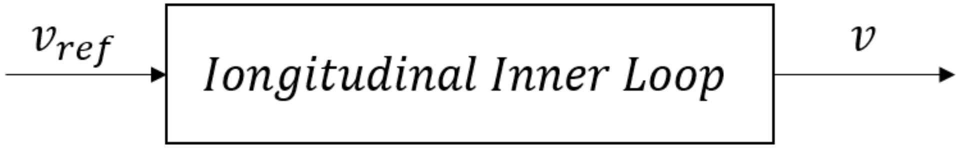


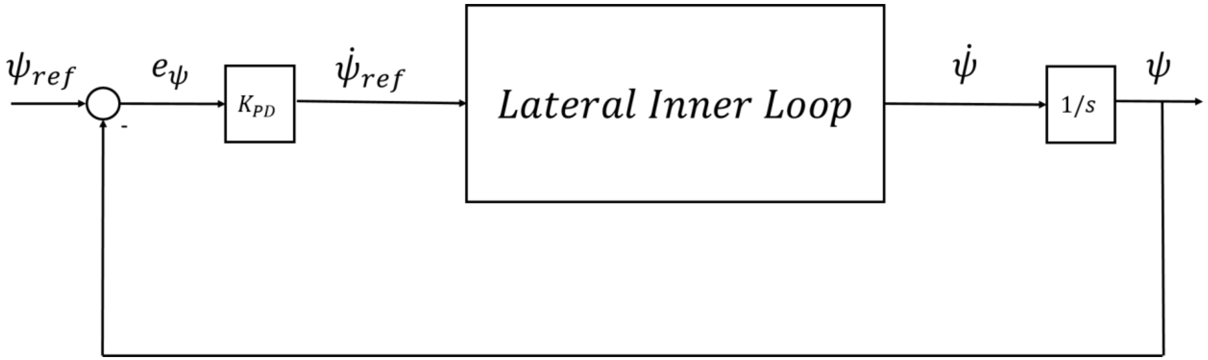
Bode Magnitude Plot for PD Outer Loop T_{ry}

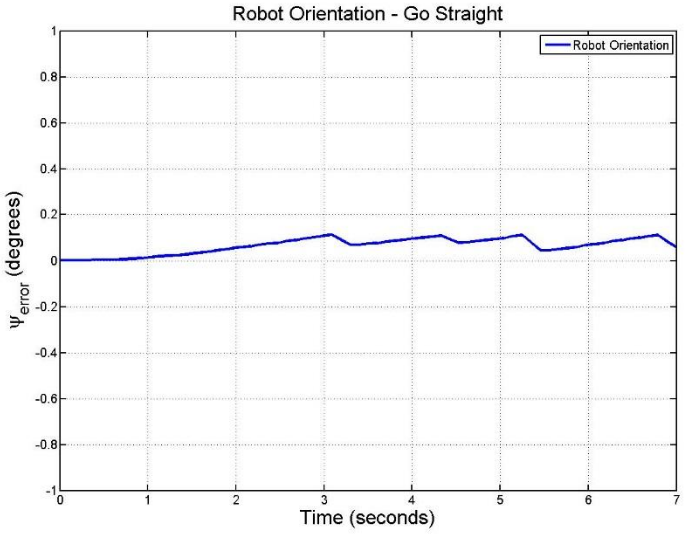


Step Response for Outer Loop T_{ru}

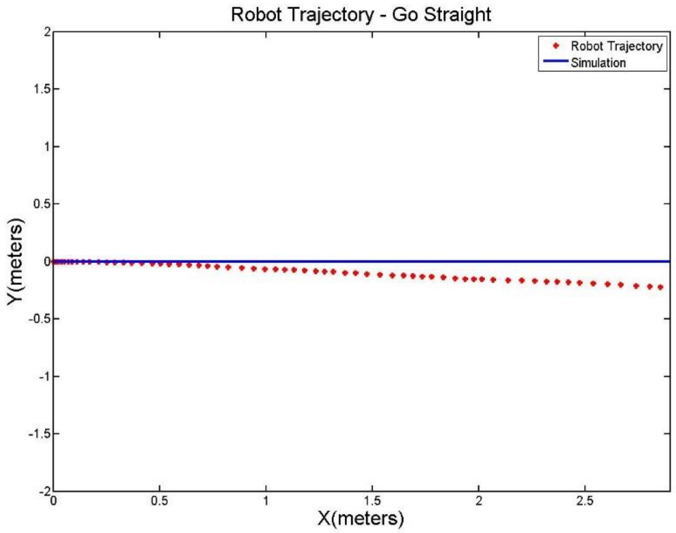
Going Along a Straight Line (v, θ Control)
(Dhaouadi, et al, 2013)







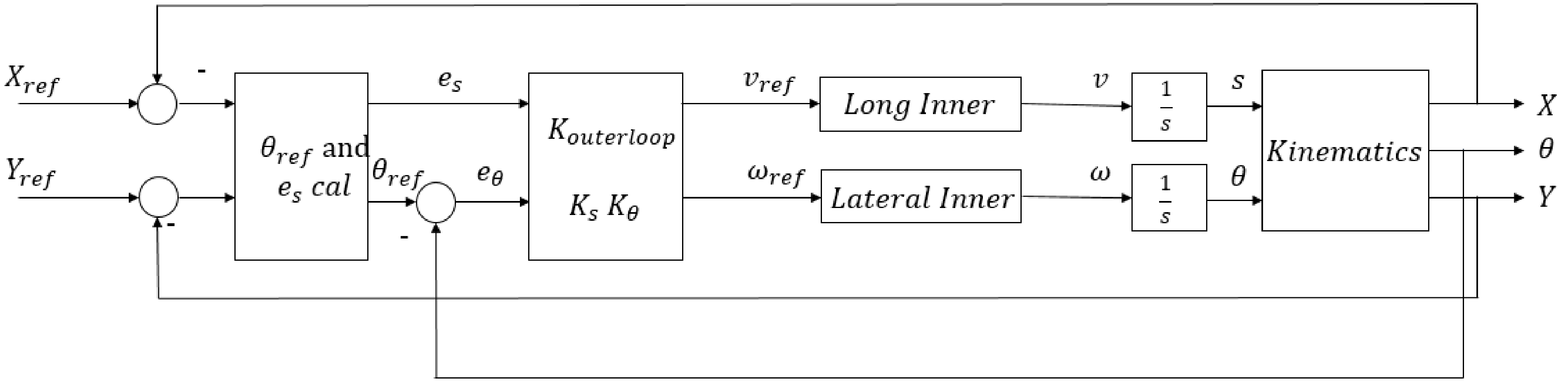
Orientation Angle Error (IMU)

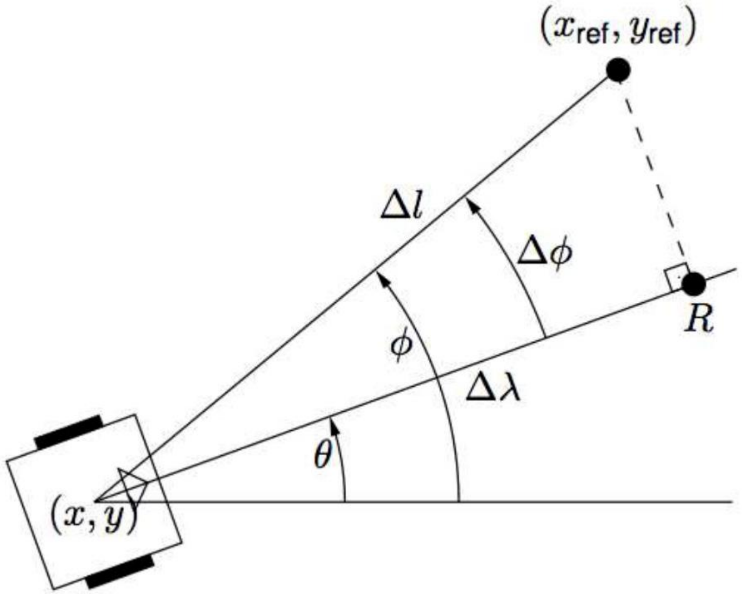


Trajectory (IMU and Encoder)

- Due to Dead Reckoning Error

Planar (x, y) Cartesian Stabilization – Algorithm
(Vieira, et.al. 2004)





Pointing angle:

$$\phi = \tan^{-1}\left(\frac{y_{ref} - y}{x_{ref} - x}\right)$$

$$e_\theta = \phi - \theta$$

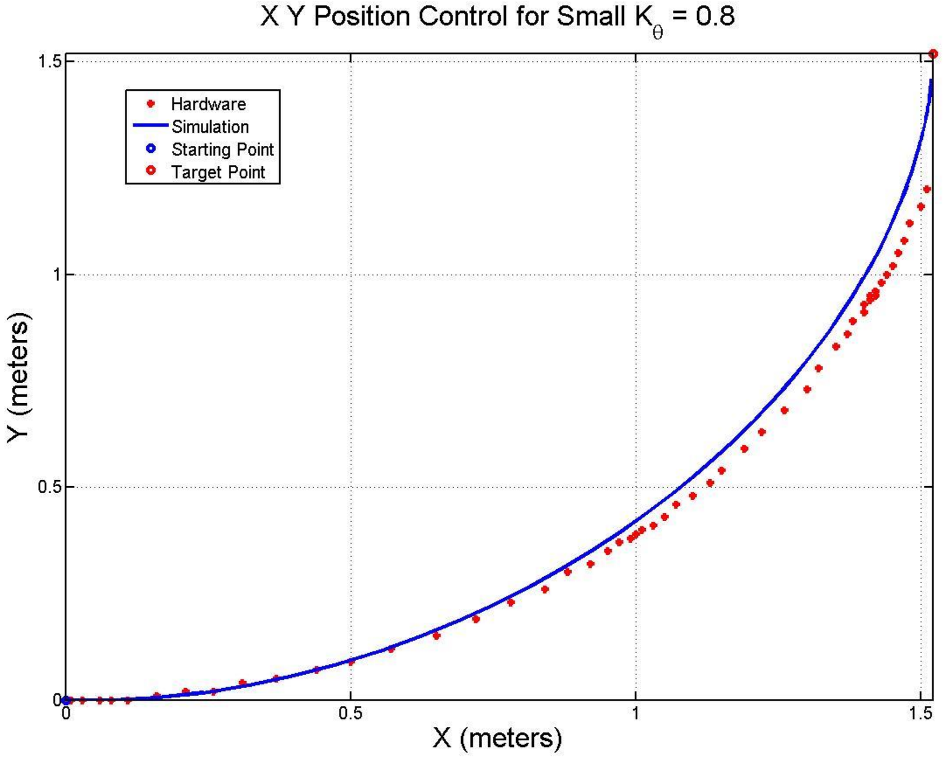
$$e_s = \Delta\lambda = \Delta l \cos \Delta\phi$$

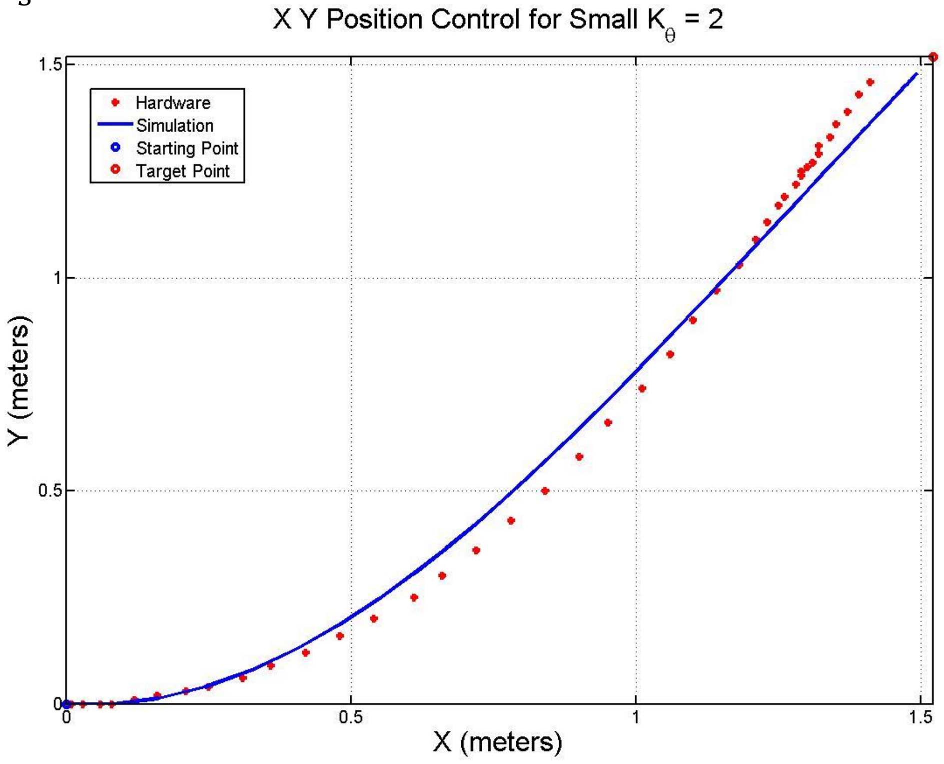
Outer Loop P controller, then send v_{ref} and ω_{ref} to inner loops:

$$v = k_s e_s \qquad \omega = k_\theta e_\theta$$

Planar (x, y) Cartesian Stabilization - Implementation

- Fixed K_s



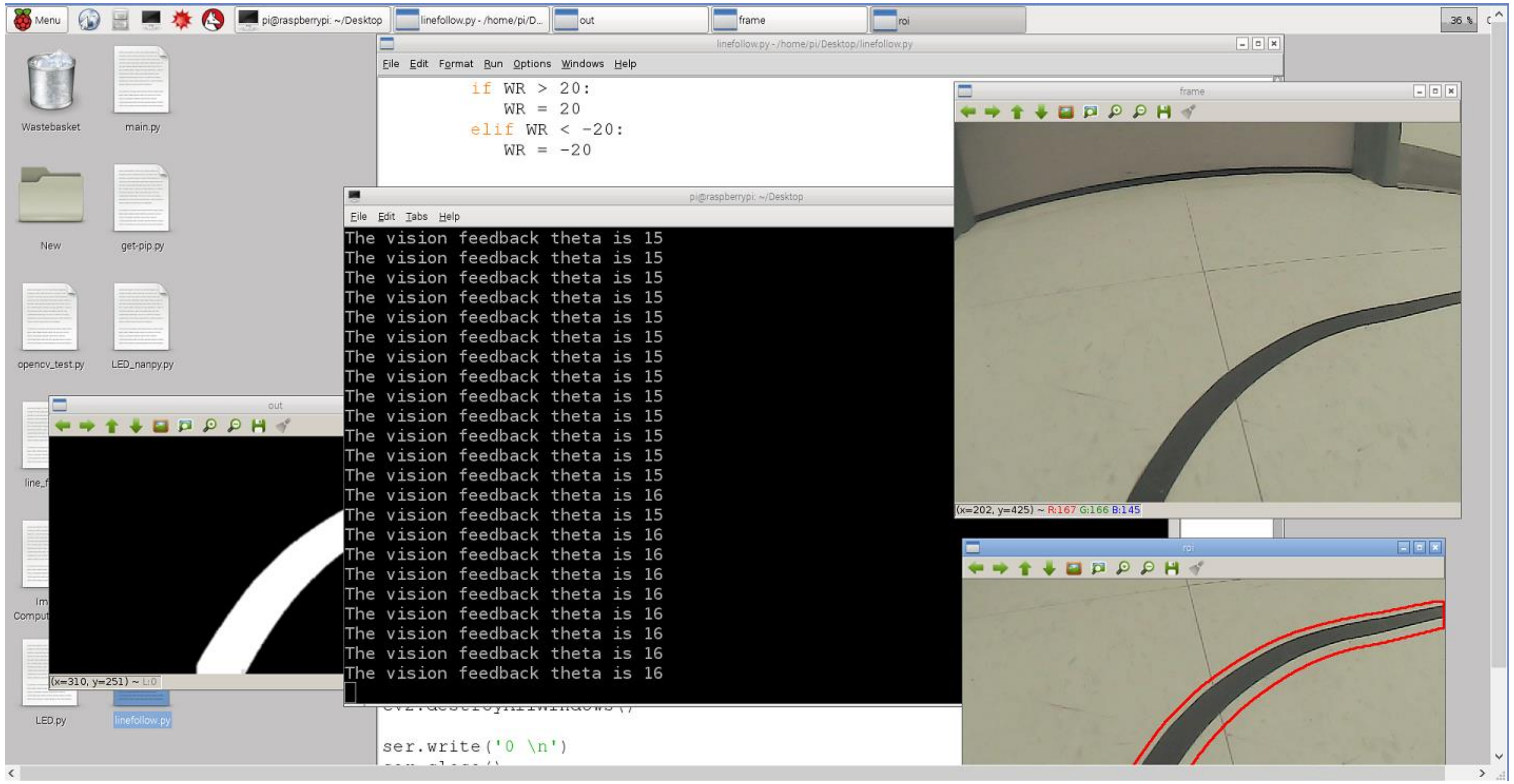


- Small K_θ ($K_\theta = 0.8$)
- Less directionally aggressive

- Large K_θ (K_θ = 2)
- Move more directly towards the target

Image Processing to Get Outer Loop ψ_{error}

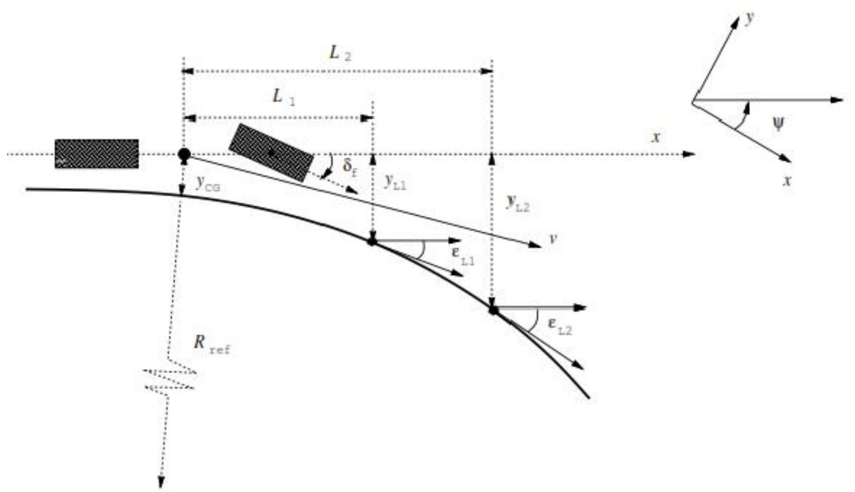
(Bradski G, Kaehler A, 2008)



- Vision subsystem offers ψ_{error} directly and send it to lower level controllers
- Outer loop frequency is limited by image processing process, which is 7.5Hz

Vision Subsystem Based Complete Model

$$\begin{bmatrix} \dot{v}_y \\ \ddot{\psi} \\ \dot{y}_L \\ \dot{\varepsilon}_L \end{bmatrix} = \begin{bmatrix} -\frac{c_f+c_r}{mv_x} & -v_x + \frac{c_r l_r - c_f l_f}{mv_x} & 0 & 0 \\ \frac{-l_f c_f + l_r c_r}{I_\psi v_x} & -\frac{l_f^2 c_f + l_r^2 c_r}{I_\psi v_x} & 0 & 0 \\ -1 & -L & 0 & v_x \\ 0 & -1 & 0 & 0 \end{bmatrix} \begin{bmatrix} v_y \\ \dot{\psi} \\ y_L \\ \varepsilon_L \end{bmatrix} + \begin{bmatrix} \frac{c_f}{m} \\ \frac{l_f c_f}{I_\psi} \\ 0 \\ 0 \end{bmatrix} \delta_f + \begin{bmatrix} 0 \\ 0 \\ 0 \\ v_x \end{bmatrix} K_L$$



$$y = \begin{bmatrix} -\frac{c_f+c_r}{mv_x} & \frac{c_r l_r - c_f l_f}{mv_x} & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} v_y \\ \dot{\psi} \\ y_L \\ \varepsilon_L \end{bmatrix} + \begin{bmatrix} \frac{c_f}{m} \\ 0 \\ 0 \\ 0 \end{bmatrix} \delta_f$$

- K_L is Disturbance

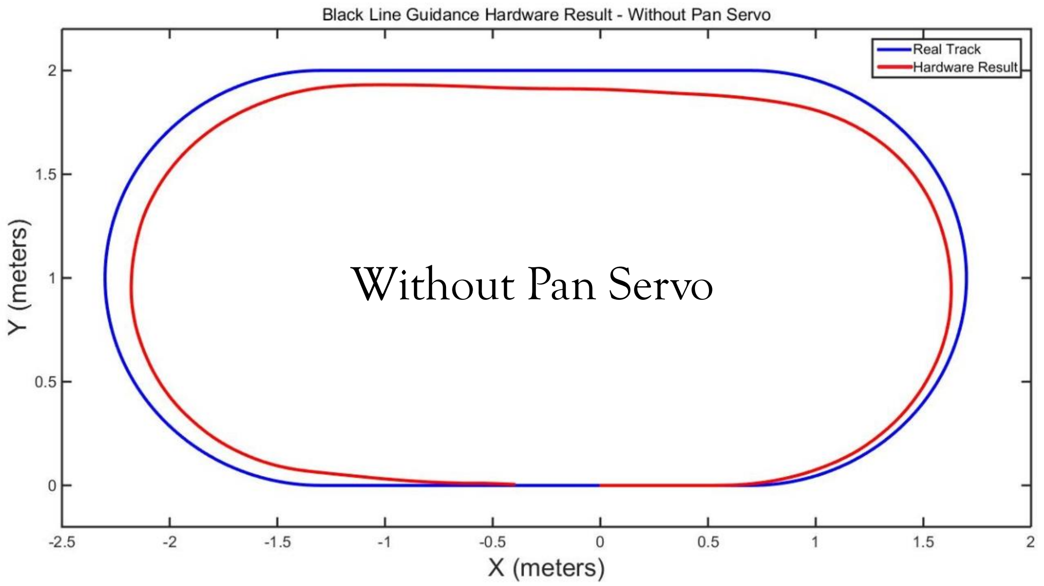
$$V_{1fs}(s) = \frac{y_L}{\delta_f} = \frac{0.06183s^2 + 0.04275s + 0.01781}{s^4 + 1.534s^3 + 1.228s^2}$$

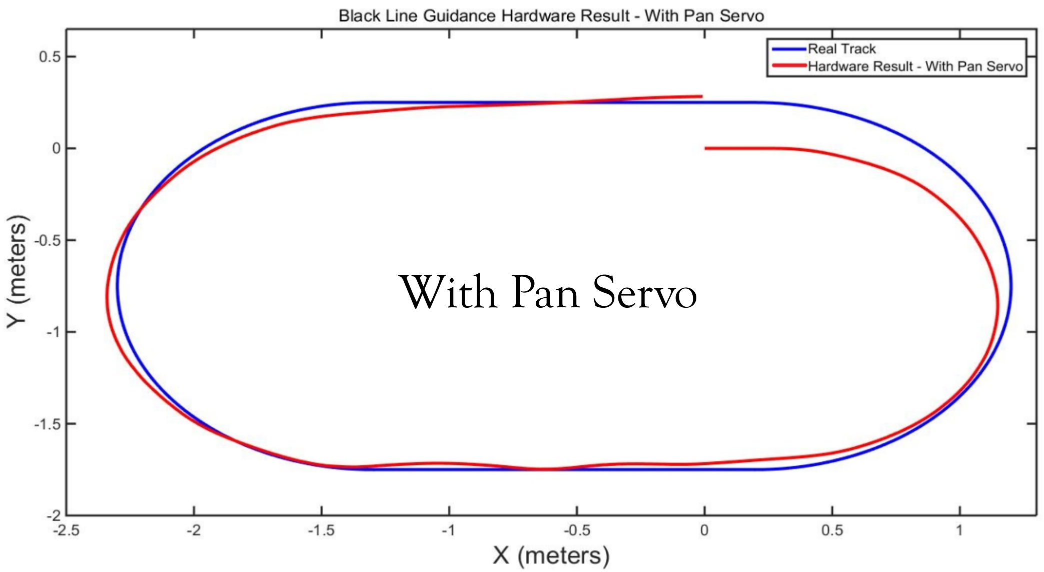
- y_L offset from the centerline at the look – ahead distance

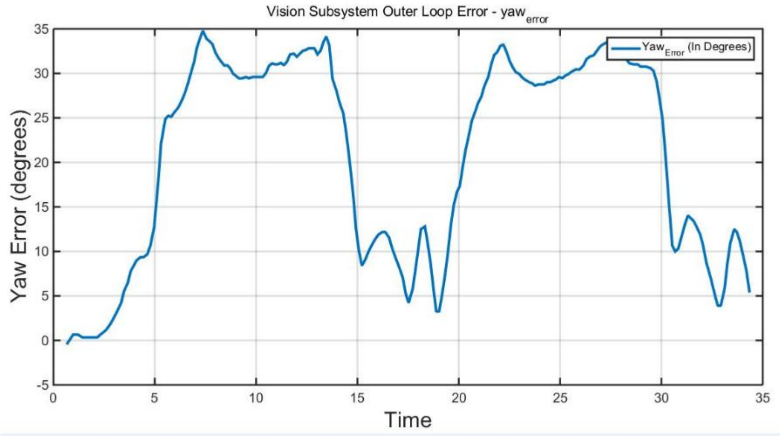
$$V_{2fs}(s) = \frac{\varepsilon_L}{\delta_f} = \frac{0.368s + 0.1781}{s^3 + 1.534^2 + 1.228s}$$

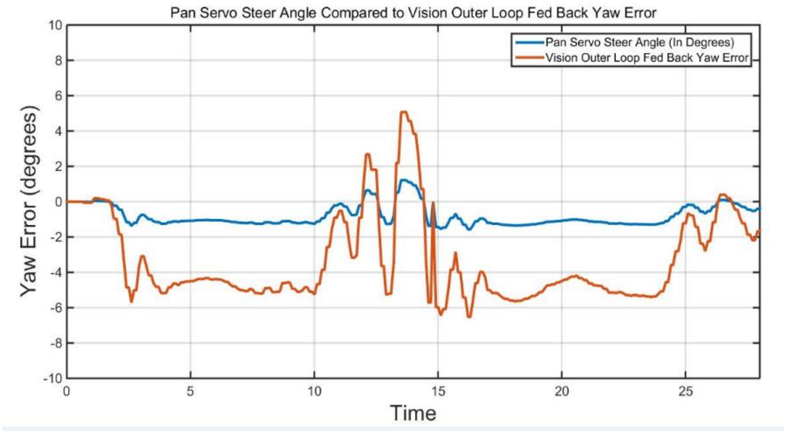
- ε_L angle between target to road and orientation of vehicle wrt the road
- L Look ahead distance at which the measurements are taken

Rear Wheel Drive Robot Finish Oval Track in Minimum Time With/Without Pan Servo

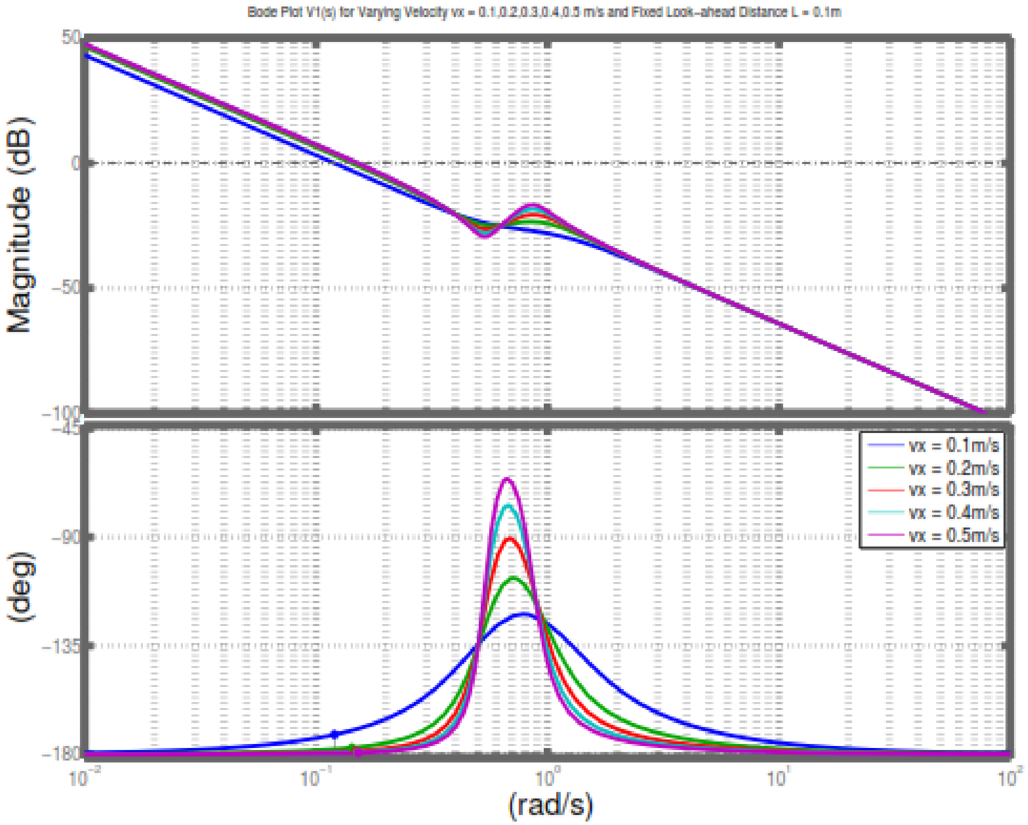


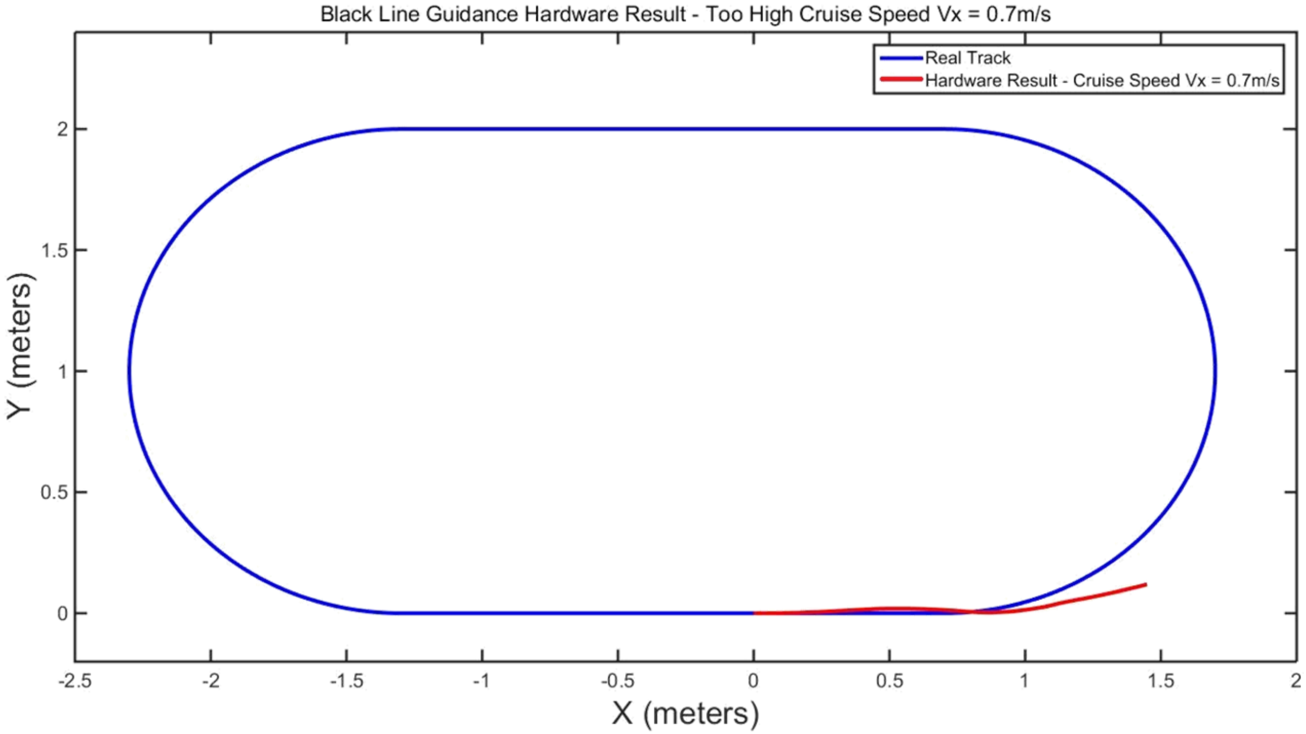






Track Following Performance with Different Cruise Speed V_x

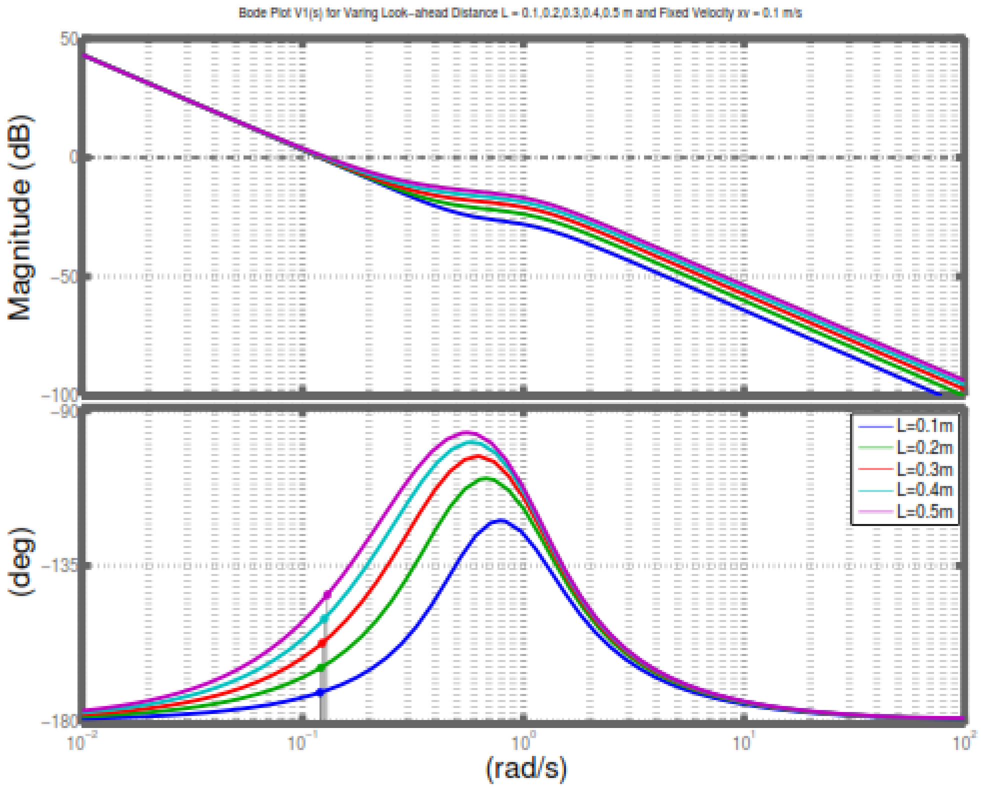


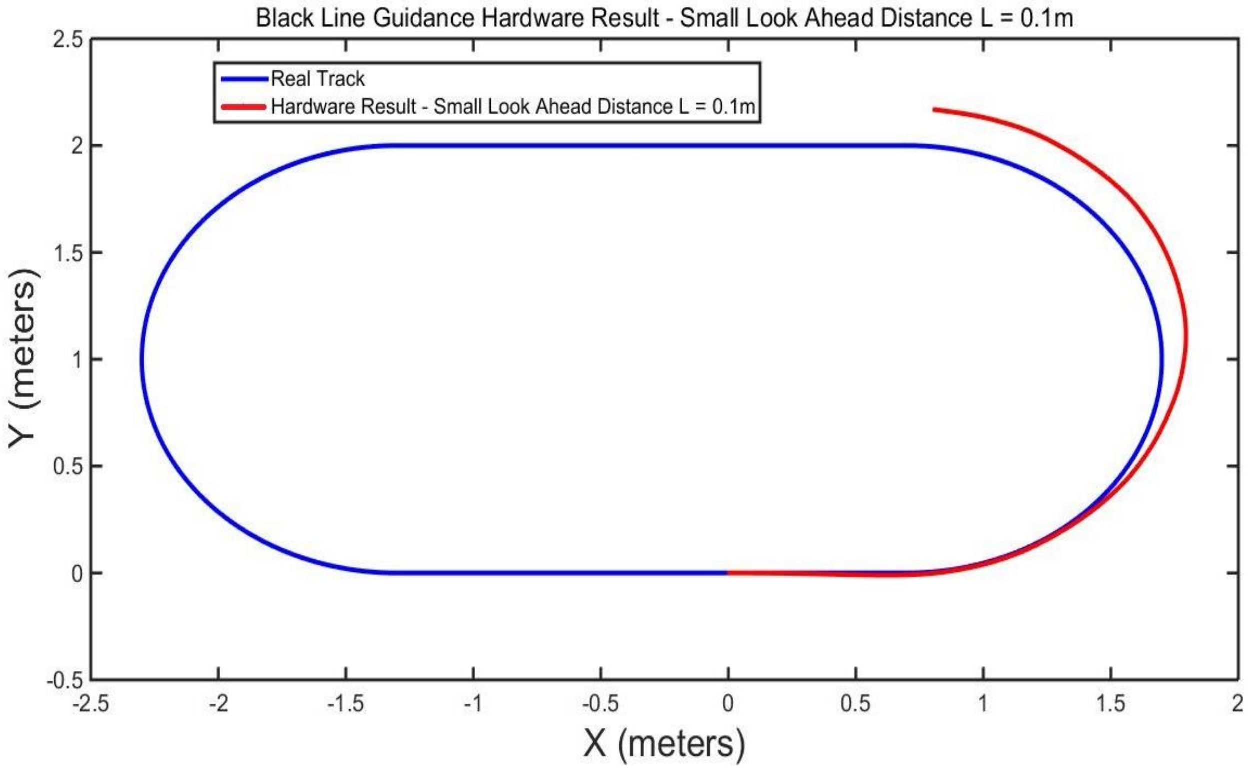


- When implementing a P controller: K = 1

- Phase Margin decreases as the robot cruise speed is increasing
- Hardware Result: Robot goes off the track with too high cruise speed ($v_x = 0.7m/s$)

Track Following Performance with Different Camera Look-Ahead Distance *L*





- ➢ When implementing a P controller: K = 1

- ➢ Phase Margin (PM) increases as the L is increasing.

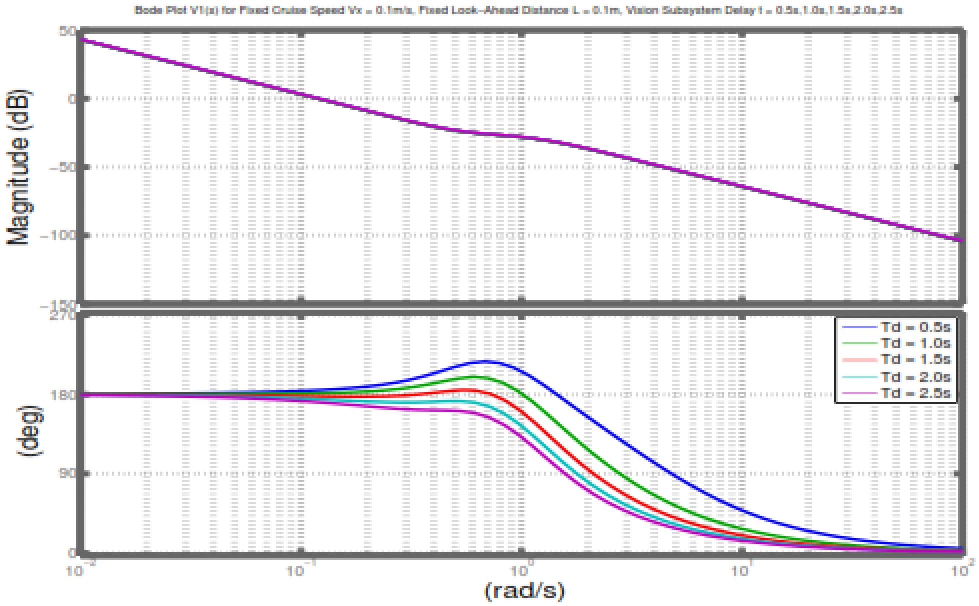
- ➢ Hardware Result: Robot goes off the track with too small camera look-ahead distance $L = 0.1m$

Track Following Performance with Different Vision subsystem delay T_d

According to Padé approximation:

$$D(s) = \frac{-0.5s + 2}{0.5s + 2}$$

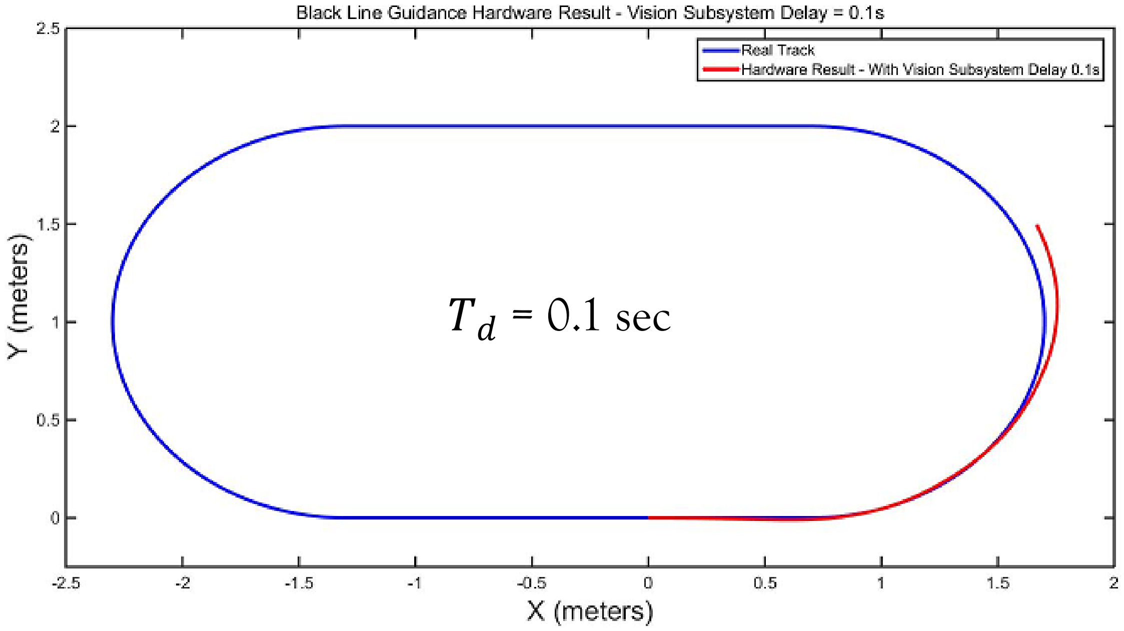
$$V_1(s)D(s) = \frac{y_L}{\delta_f} = \frac{-0.06183s^3 + 0.2046s^2 + 0.1532s + 0.07124}{s^5 + 5.534s^4 + 7.362s^3 + 4.912s^2}$$



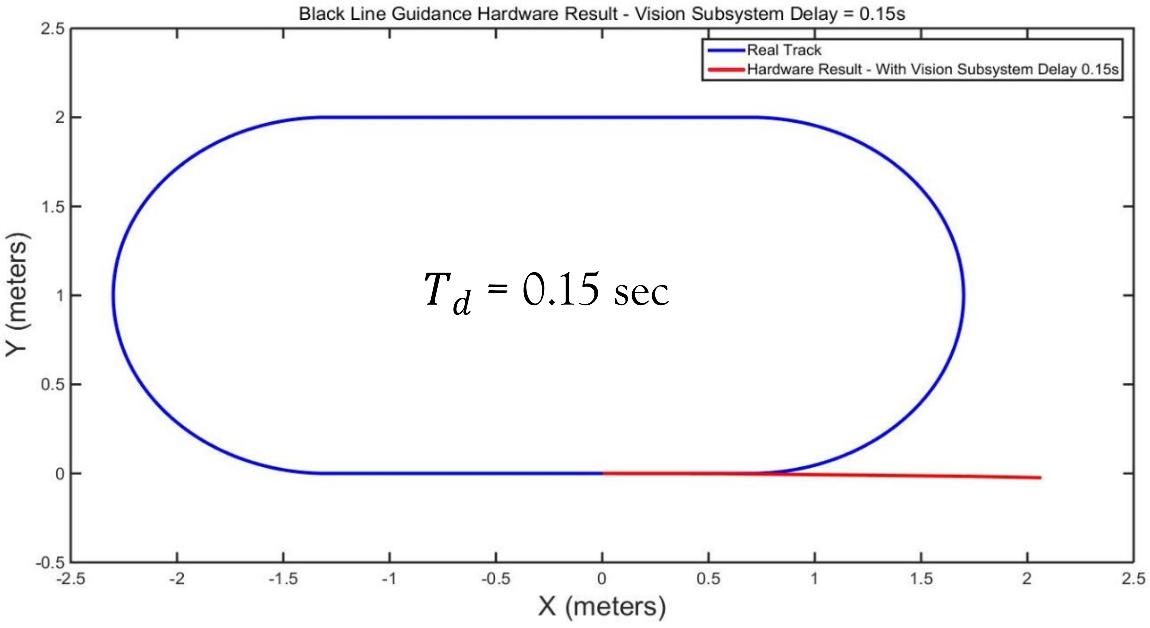
- With small vision subsystem delay T_d phase margin is very small
- With large vision subsystem delay T_d, L has a negative phase margin
- When implementing a P controller

K = 1

Track Following Performance with Different Vision subsystem delay T_d (Trajectory)



T_d = 0.1 sec



T_d = 0.15 sec

When we increases the delay from 0.1s to 0.15s

- Without vision subsystem delay (T_d = 0s), outer loop frequency is 7.52 Hz
- Without vision subsystem delay (T_d = 0.1s), outer loop frequency is 4.28Hz
- Without vision subsystem delay (T_d = 0.15s), outer loop frequency is 3.35Hz

LIDAR Hardware Description

- ➢ LIDAR I'm using:

XV 11 Hacked LIDAR

- ➢ A better LIDAR:

Hokuyo URG-04LX-UG01

- Price: $80
- Scan range: 0.2 to 6.0 meters
- Scan Frequency: 5.5 Hz
- Accuracy: ±80 mm
- Angular Resolution: 0.52°

- Price: $1115
- Scan range: 0.1 to 5.6 meters
- Scan Frequency: 10.0 Hz
- Accuracy: ±30mm
- Angular Resolution: 0.35°

SLAM Problem Definition

Given

- The robot's controls

$$u_{1:T} = \{u_1, u_2, u_3 \ldots, u_T\}$$

- Observations

$$z_{1:T} = \{z_1, z_2, z_3 \ldots, z_T\}$$

Wanted

- Map of the environment

$$m$$

- Path of the robot

$$x_{0:T} = \{x_0, x_1, x_2 \ldots, x_T\}$$

Estimate the robot's path and the map

$$p(x_{0:T}, m \mid z_{1:T}, u_{1:T})$$

distribution path map given observations controls

f -motion equation

u -control inputs

w -Input noise

g -observation equation

y -observation data

n -observation noise

Motion Model

- The motion model describes the relative motion of the robot

$$p(x_t \mid x_{t-1}, u_t)$$

distribution new pose given old pose control

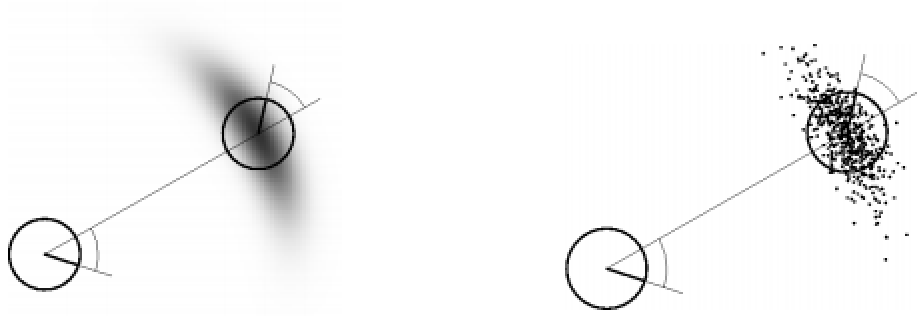
Pose: $x_k = [x, y, \psi]_k$

Motion equation f: $x_{k+1} = x_k + \Delta x_k + w_k$

Input Noise: w_k (Gaussian Noise)

- Gaussian model

- Non-Gaussian model



Non Gaussian Noise: Salt and Pepper Distribution

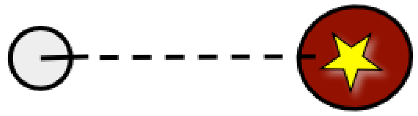
Observation Model

The observation or sensor model relates measurements with the robot's pose

$$p(z_t \mid x_t)$$

distribution observation given pose

Gaussian model



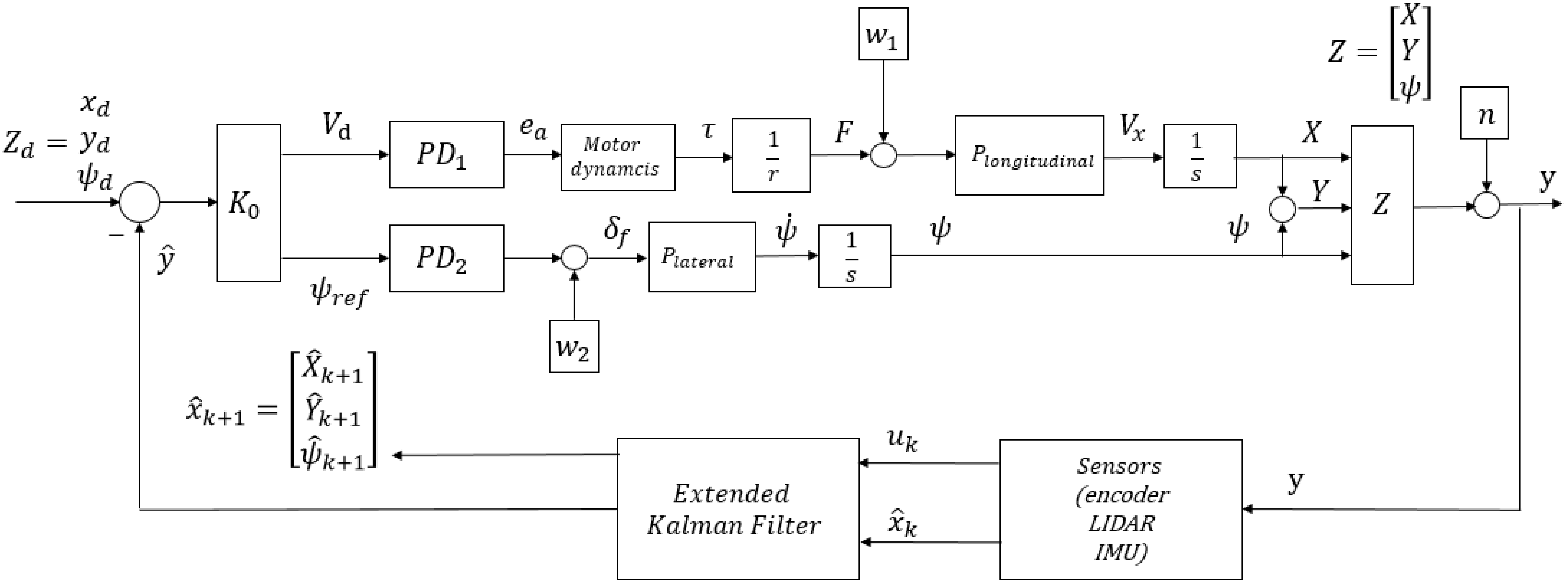
$L_k = [L_{k,x} , L_{k,y}]$ is a 2D landmark

Observation Equation g:

$$\begin{bmatrix} r \\ \theta \end{bmatrix}_k = \begin{bmatrix} \sqrt{\|x_k - L_k\|2} \\ tan^{-1} \frac{L_{k,y} - x_{k,y}}{L_{k,x} - x_{k,x}} \end{bmatrix} + n_k$$

- f and g are linearized around $\hat{x}_{k-1}$ *and* $\hat{x}_k$
- Then apply Kalman Filter

Block Diagram – Extended Kalman Filter (EKF)

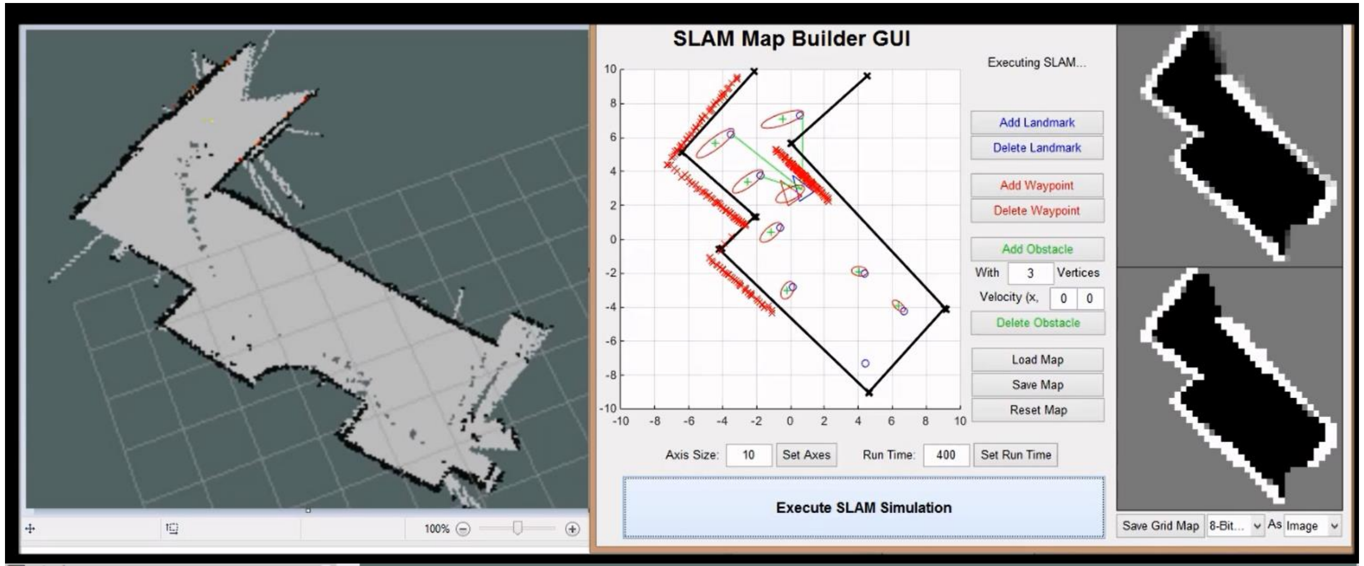


Pose Estimation for nonlinear system

Self Build Indoor Experiment Area (GWC 2nd Floor)

Robot has the ability to map a 26 m^2 environment in 38 seconds.

Simulation and Implementation Results for Mapping this Area

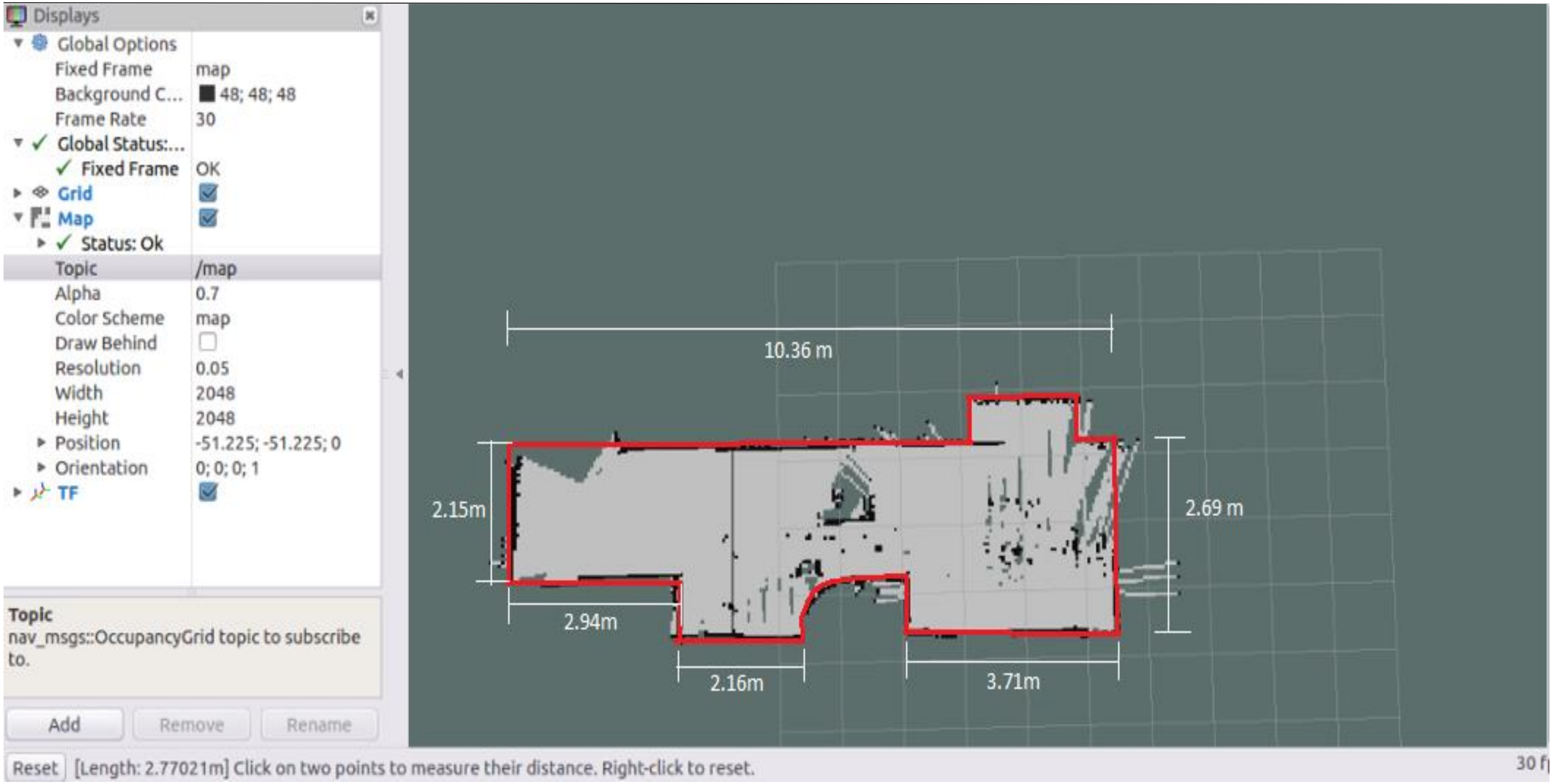


Simulation Result

Implementation Result

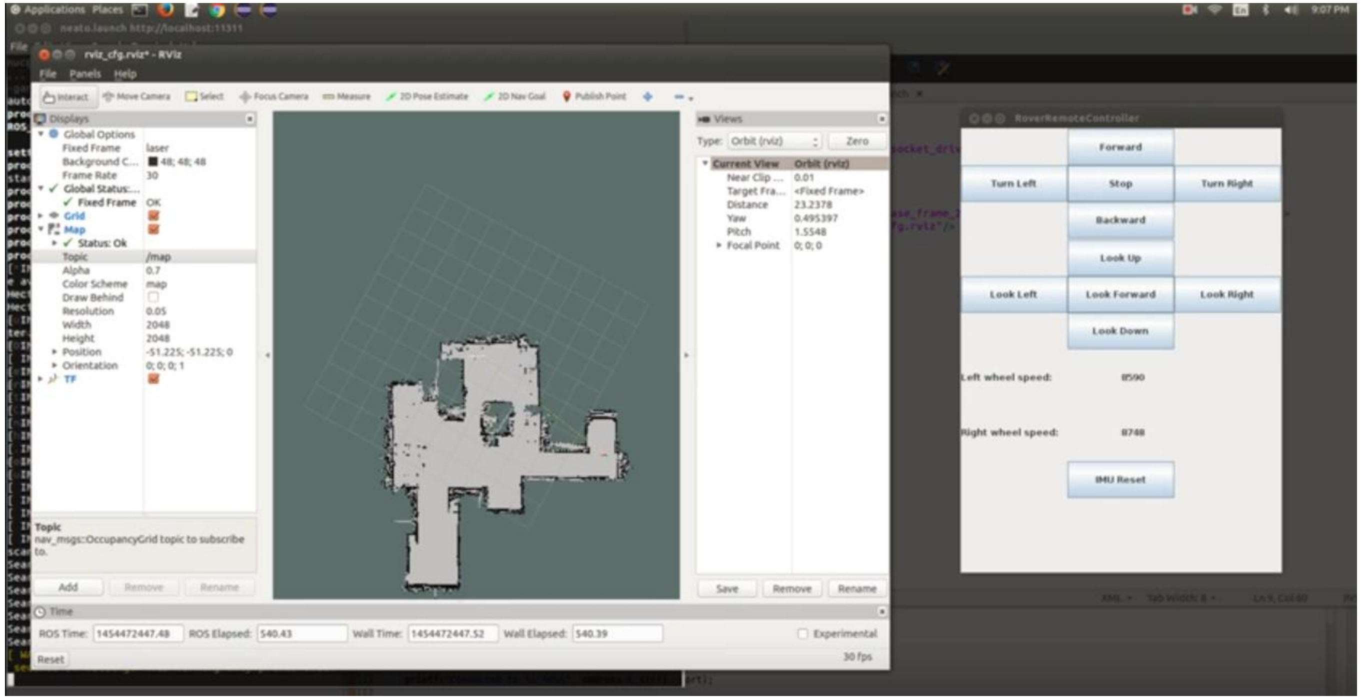
- horizontal accuracy : 5.40%
- vertical accuracy : 2.97%

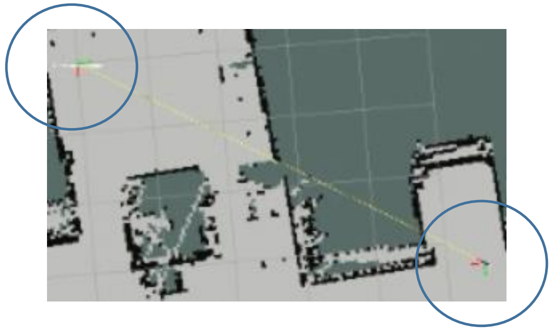
Comparison Between Real Floor Plan and Generated 2D Grid Map



Mapping Duo's house, robot was controlled manually by GUI pedals (on the right)

- Map the unknown environment
- Localize robot
- Real-time capable
- Saving GeoTiff maps





Real time position of the robot

Please see demo on Youtube:
https://www.youtube.com/watch?v=750z3U4tSAA

When Will Something Go Wrong (Turning too Fast)

➢ Map of CenterPoint Building Floor 4 Computer Science Lab and Hallway

➢ <u>Lack of scan frequency</u>

Future Works and Studies

- Localization Development of a lab-based localization system using a variety of technologies (e.g. USB cameras, depth sensors, LIDAR, ultrasonic, etc.).
- On-board Sensing Addition of multiple on board sensors; e.g. additional ultrasonic, depth sensors (Kinect), 3D LIDAR, GPS, cameras, etc.
- Advanced Image Processing Use of advanced image processing and optimization algorithms; e.g. Implementations of OpenCV and OpenGL and vision based mapping and localization.
- 3D unknown environment reconstruction. In this thesis, the 2D indoor unknown environment mapping was well discussed.
- Modelling and Control More accurate dynamic models and controls laws.
- Control-Centric Vehicle Design Understanding when simple control laws are possible and when complex control laws are essential.

Thank you

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Thank you

Any Questions?