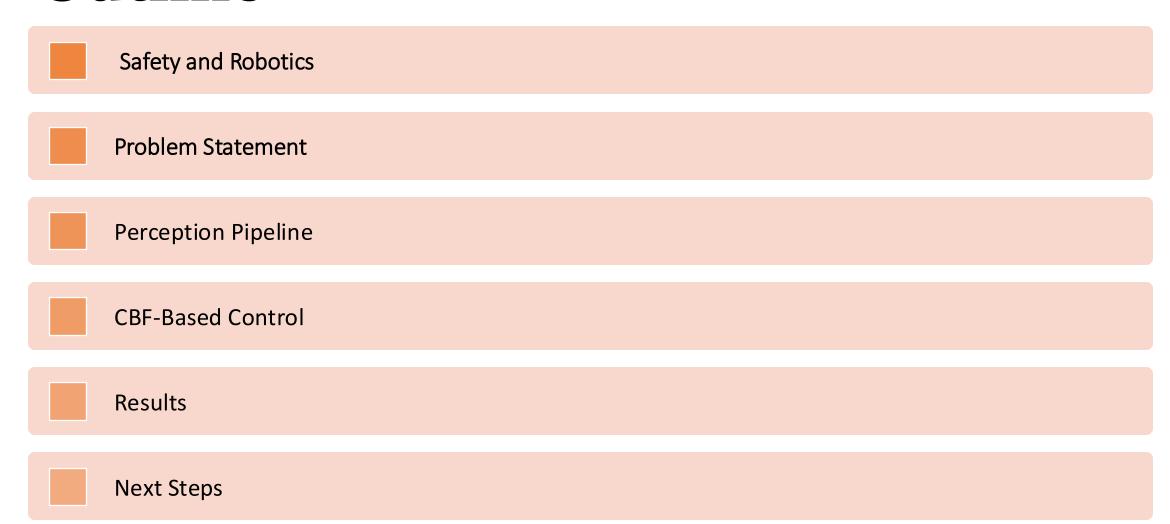


Real-Time Obstacle Detection and Avoidance using Low-Level CBF/CLF and CBF/PID Controllers

Nicolas Hernandez

Outline





Safety and Robotics



Motivation

Increasing demand for autonomous systems in dynamic environments highlights the need for real-time safe collision avoidance techniques

- The U.S. autonomous vehicle market has an expected annual growth of 27.5% [1]
- Self-driving vehicles are more than twice as likely as traditional vehicles to get into auto accidents [2]"
- US Global humanoid robot has an expected annual growth of 15.57% [3]

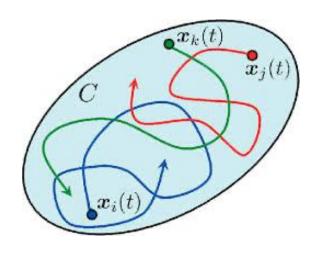
• A robot arm at Tesla's factory reportedly attacked and injured an engineer[4]





How do we define safety?

$$\dot{x} = f(x) + g(x)u$$
 $x = \begin{bmatrix} p_x \\ p_y \end{bmatrix}$



• The safe set C is defined everywhere in the state space except for the obstacle.

$$\mathcal{C} = \{ x \in \mathbb{R}^n : b(x) \le 0 \}$$

• Safety means the set is forward invariant i.e. if the state starts in C it never leaves C

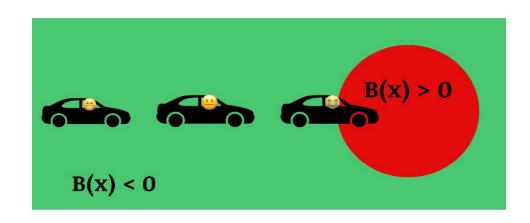
$$x(0) \in \mathcal{C} \implies x(t) \in \mathcal{C}, \ \forall t \ge 0$$



Control Barrier Functions (CBFs)

$$b(x) = R^2 - \left[(p_x - x_{\text{obs}})^2 + (p_y - y_{\text{obs}})^2 \right]$$

• A Control Barrier Function (CBF) defines the safe and unsafe regions



• We define the unsafe region or obstacle as a circle

s.t.
$$\frac{db}{dt} \ge -\alpha b(\mathbf{x})$$
 $\frac{db}{dt} = \frac{\partial b}{\partial \mathbf{x}} \left(f(\mathbf{x}) + g(\mathbf{x}) \mathbf{u} \right)$

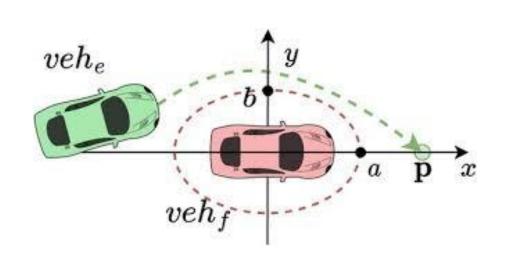
• We ensure safety by imposing a constraint on the CBF

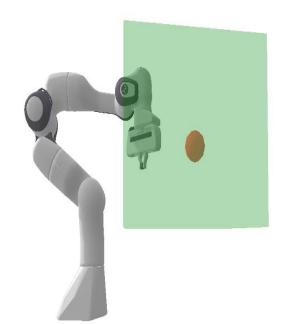


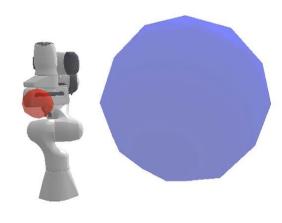
Applications of CBF's

Autonomous Driving and Locomotion

Robot Manipulators









Problem Statement

In a partially unknown environment, autonomously navigate from a starting location to a goal while preventing collisions with unforeseen and Dynamic obstacles.

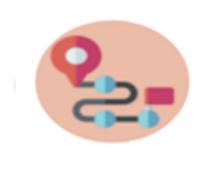


Four Steps of Autonomous Navigation

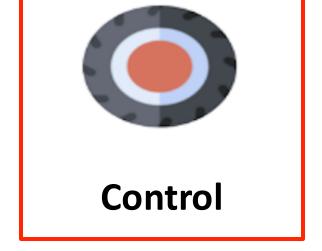


Localization





Path Planning



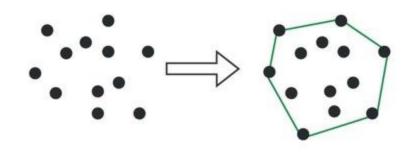


Perception Pipeline



Perception Pipeline





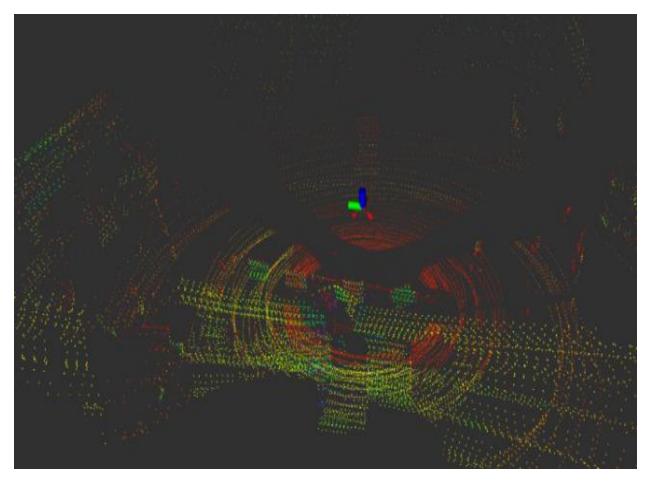
Filtering and Clustering

Shape Wrapping



Filtering Lidar Points

- Original Point Cloud
 ➤ ~ 1500 data points
- Down-sampled using Voxel Grid Filter
 ➤ ~ 800 data points
- Filter points outside a 2x1 meter box from the Plant
 - > ~ 150 data points
- Filter Out Floor(1.2 Meters from Z Plane)
 - > ~ 100 data points



Unfiltered Lidar Data From Humanoid



Humanoid Blind Spots



Top Down View of Lidar Data

Back View of Lidar

FOV of Lidar and Camera

$$d = h \cdot \tan(\theta) = 1.2 \cdot \tan(59^\circ) \approx 1.997 \text{ m}$$
 $d = (h - h_o) \cdot \tan(\theta)$



Vertical position (m)

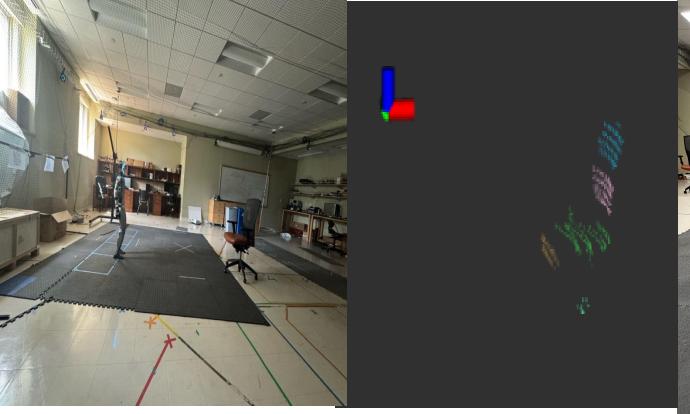
Clustering Lidar Points

What we see

What the Humanoid Detects

What we see

What the Car detects



• Latency Humanoid: (.3s)

• Latency 1/10 Car: (.8s)

Horizontal position (m)

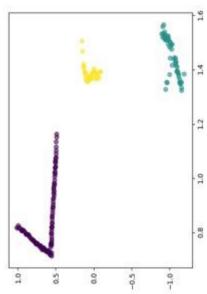


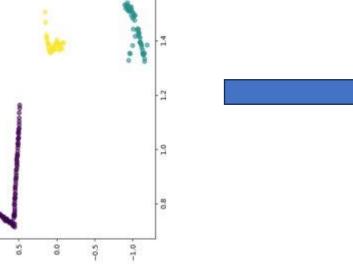
Obstacle Shape Wrapping

Box Method

Compute the minimum and maximum x and y coordinates of the cluster.

Define box vertices and calculate the centroid.



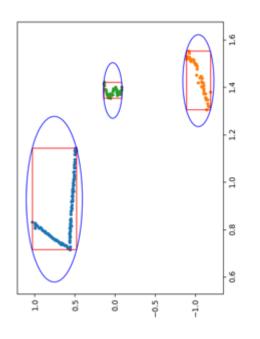


$$X_{1} = min(x_{1}, x_{2}, ..., x_{n})$$

$$X_{2} = max(x_{1}, x_{2}, ..., x_{n})$$

$$Y_{1} = min(y_{1}, y_{2}, ..., y_{n})$$

$$Y_{2} = max(y_{1}, y_{2}, ..., y_{n})$$



Horizontal position (m)

$$x_{C} = \frac{X_{min} + X_{max}}{2}$$

$$y_{C} = \frac{Y_{min} + Y_{max}}{2}$$

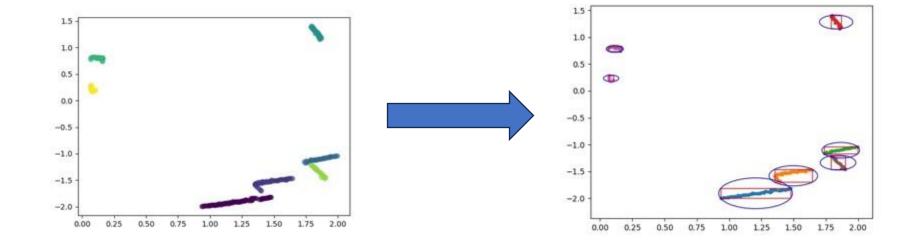


Obstacle Shape Wrapping

Integration into CBF filter

•
$$X_C = X_{obs}$$

•
$$Y_C = Y_{obs}$$



radius =
$$\sqrt{(x_{\text{obs}} - x_{\text{max}})^2 + (y_{\text{obs}} - y_{\text{max}})^2}$$



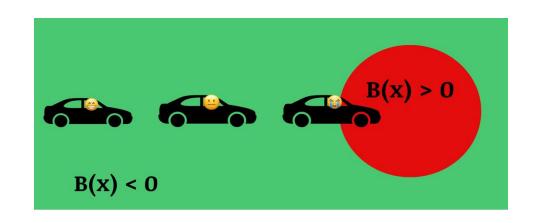
CBF Based Control



Control Barrier Functions (CBFs)

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• A Control Barrier Function (CBF) defines the safe and unsafe regions



• We define the unsafe region or obstacle as a circle

s.t.
$$\frac{db}{dt} \ge -\alpha b(\mathbf{x})$$
 $\frac{db}{dt} = \frac{\partial b}{\partial \mathbf{x}} \left(f(\mathbf{x}) + g(\mathbf{x}) \mathbf{u} \right)$

• We ensure safety by imposing a constraint on the CBF



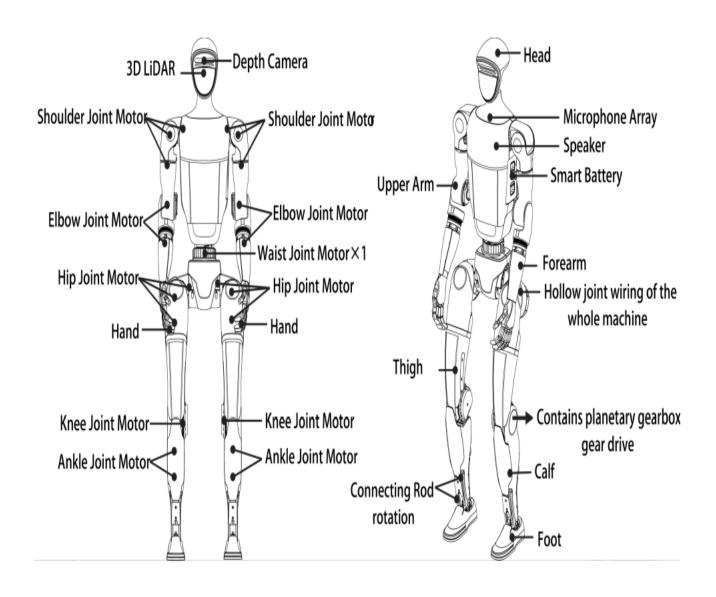
1/10 Scale Ackerman Car



- o NVIDIA Jetson TX2-NX module
 - Quadcore ARM Cort ex CPU
 - 2.0 GHz(typical:~1.5 GHz)
- Sensors: IMU, LiDAR,
 Depth Camera, Odometer
- Localizes using EKFSensor Fusion (IMU + LiDAR + Odometry)



G1- Humanoid



- 43 Degrees of Freedom (DoF)
- NVIDIA Jetson Orion module
 - Octa-core Arm Cortex-CPU
 - 2.0 GHz (typical: ~1.6 GHz)
- Sensors: Imu,Lidar,Depth
 Camera, Odometer
- Localizes usingOdometer in WorldFrame



Dynamics

$$\dot{x} = f(x) + g(x)u$$

Single Integrator Dynamics

$$x = egin{bmatrix} p_x \ p_y \end{bmatrix}, \quad u = egin{bmatrix} v_x \ v_y \end{bmatrix}, \quad \dot{x} = egin{bmatrix} v_x \ v_y \end{bmatrix}$$

$$f(x) = 0$$
 and $g(x) = I$

Unicycle Dynamics

$$x = \begin{bmatrix} p_x \\ p_y \end{bmatrix}, \quad u = \begin{bmatrix} v_x \\ v_y \end{bmatrix}, \quad \dot{x} = \begin{bmatrix} v_x \\ v_y \end{bmatrix} \qquad \qquad x = \begin{bmatrix} \theta \\ p_x \\ p_y \end{bmatrix}, \quad u \in R^{2 \times 1}, \quad u = \begin{bmatrix} \omega \\ v \end{bmatrix}, \quad \dot{x} = \begin{bmatrix} \omega \\ v \cos(\theta) \\ v \sin(\theta) \end{bmatrix}$$

$$\dot{x} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & \cos(\theta) \\ 0 & \sin(\theta) \end{bmatrix} \begin{bmatrix} \omega \\ v \end{bmatrix}$$

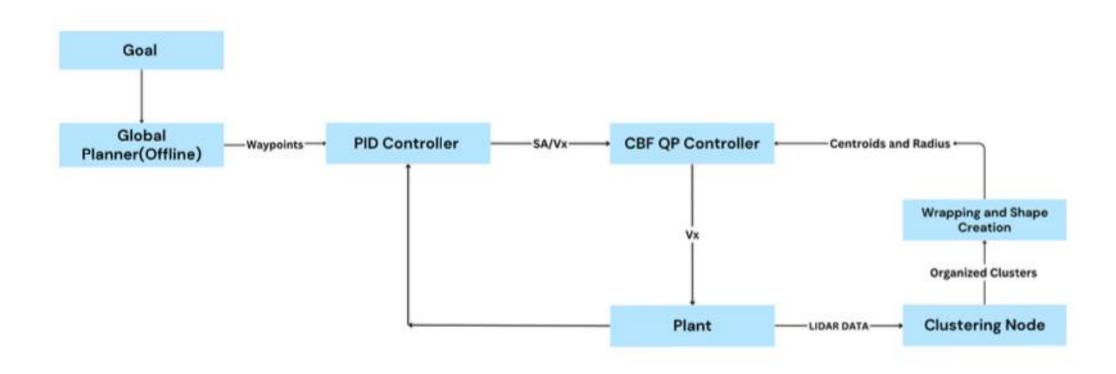
	Unicycle	Single Integrator
Humanoid	\bigcirc	\bigcirc
1/10 Scale Car	\bigcirc	



PID/CBF Quadratic Program (QP) Controller



Reach & Avoid Pipeline



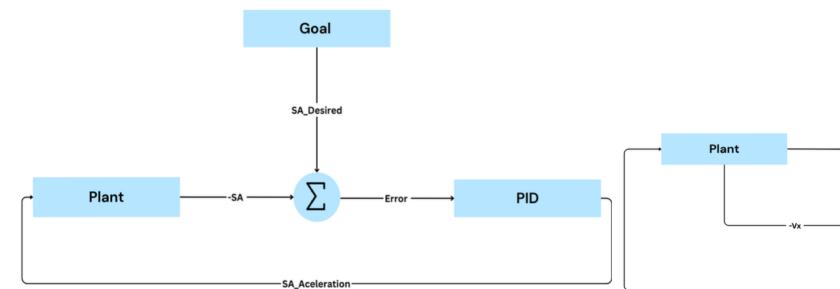


PID Formulation

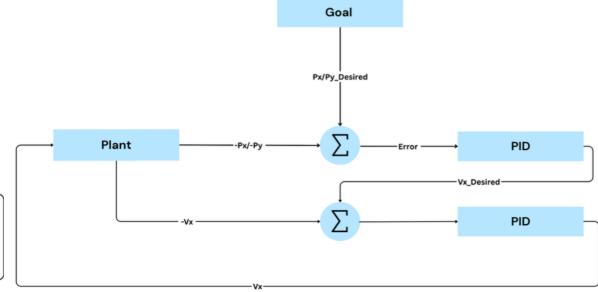
Our PID Controllers controls States
$$x = \begin{bmatrix} \theta \\ p_x \\ p_y \end{bmatrix}$$

 $\begin{vmatrix} v \\ p_x \\ p_y \end{vmatrix}$ through control Inputs

$$u = egin{bmatrix} \omega \ v \end{bmatrix}$$







Position Controller



QP Formulation

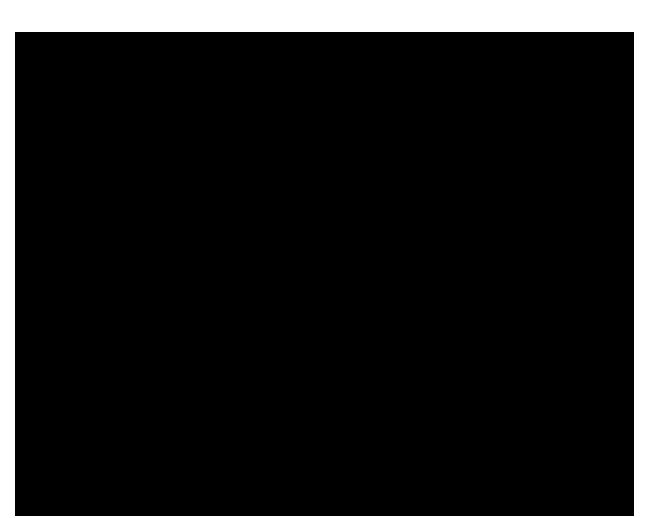
Goal: Find U that is as close as possible to the PID signal, while ensuring safety by satisfying the barrier function constraint.

$$\mathbf{u} = \min \|\mathbf{u} - \mathbf{u}_{\text{PID}}\|^2 \quad \text{s.t.} \quad \frac{db}{dt} \ge -\alpha b(\mathbf{x})$$

where
$$\frac{db}{dt} = \frac{\partial b}{\partial \mathbf{x}} \left(f(\mathbf{x}) + g(\mathbf{x}) \mathbf{u} \right)$$



PID/CBF Sticking Point 1/10 Car



Sticking Point: a non-ideal equilibrium point where the dynamics or constraints prevent the plant from naturally moving towards the goal.

CBF:
$$b(x) = R^2 - \left[(p_x - x_{\text{obs}})^2 + (p_y - y_{\text{obs}})^2 \right]$$

CBF Constraint Unicycle Dynamics

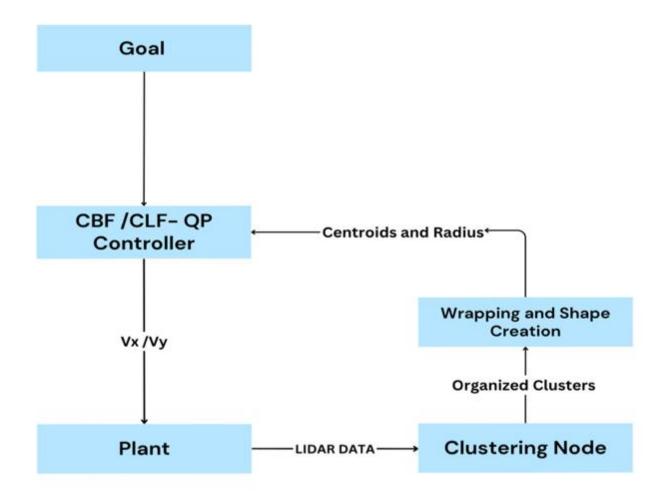
$$[2(p_x - x_{\text{obs}})\cos\theta + 2(p_y - y_{\text{obs}})\sin\theta]v + 0 \cdot \omega \ge 0$$



CLF/CBF QP Controller



Reach & Avoid Pipeline





Control Lyapunov Function (CLF)

$$V(x) = \alpha \left((p_x - x_{\text{goal}})^2 + (p_y - y_{\text{goal}})^2 \right)$$

- V(x) > 0 for all $x \neq x_{goal}$, and $V(x_{goal}) = 0$,
- $V(x) \to \infty$ as $||x x_{goal}|| \to \infty$,
- $\dot{V}(x) = \nabla V(x)^T (f(x) + g(x)u) < 0$ for some control input u.



QP Formulation

Goal: Find U that is as close as possible to the CLF signal, while ensuring safety by satisfying the barrier function constraint.

$$\min_{u} \quad (u - u_{\text{CLF}})^T (u - u_{\text{CLF}})$$

s.t.
$$\nabla_x b_i(x)(f(x) + g(x)u) \ge -\alpha b_i(x), \quad \forall i = 1, \dots, N$$

$$u_{\text{CLF}} = \alpha \begin{bmatrix} (p_x - x_{\text{goal}}) \\ (p_y - y_{\text{goal}}) \end{bmatrix}$$



CBF for Multiple Obstacles

$$b(x) = R^{2} - \left[(p_{x} - x_{\text{obs}})^{2} + \left((|p_{y} - y_{\text{obs}}| + 1)^{3} - 1 \right) \right]$$

- Cube term emphasizes obstacles directly in front of the vehicle, making the system more sensitive to obstacles aligned with its forward trajectory.
- If the y term is below 1, when cubed, it becomes smaller. In order to keep the steepness of the y-dependent term, 1 was added in and then subtracted after taking the cube
- Obstacles farther to the side contribute less, because the squared term grows more slowly, allowing the system to place stronger constraints on objects within the forward motion of the plant



QP Constraints for Multiple Obstacles

$$\min_{u} (u - u_{\text{CLF}})^{T} (u - u_{\text{CLF}})$$
 s.t.
$$\nabla_{x} b_{i}(x) (f(x) + g(x)u) \geq -\alpha b_{i}(x), \quad \forall i = 1, \dots, N$$

For every detected obstacle, a new constraint is added to the QP to ensure safety

$$\alpha_i = \frac{\text{safety gain}}{(1 + y_{\text{centroid}i})^3} \quad i = 1, 2, \dots, N$$

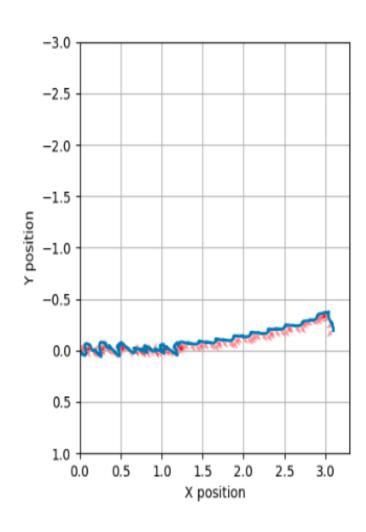
Alpha weights the constraints and prioritizes obstacles aligned with the trajectory of the car.



Results



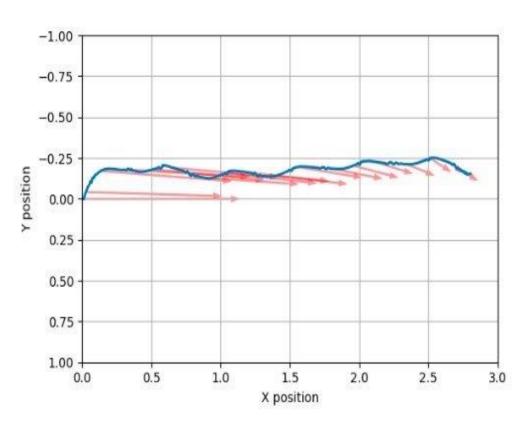
No Obstacle CBF/CLF



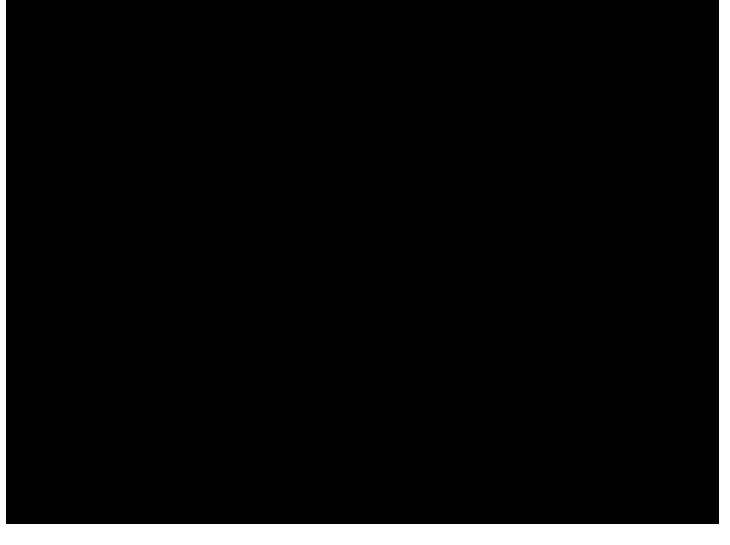




No Obstacle PID



(b) VxVy PID Controller





Preliminary Remarks

- **Odometry drift** affected the smoothness and accuracy of trajectory plots
- LiDAR range limited: Obstacles >2 m ahead or ±1 m sideways were ignored
- Safety gain set to 1.2 for all runs
- **CBF response triggered** only when safety constraint was violated

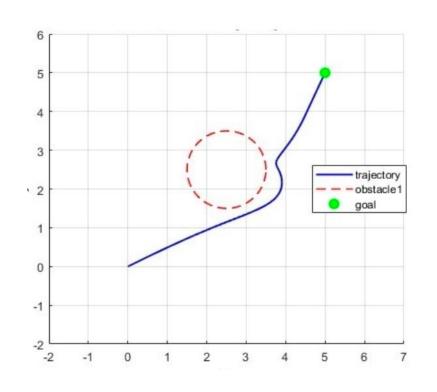
• Velocity plots down sampled: Only 1 in 16 commands shown for clarity

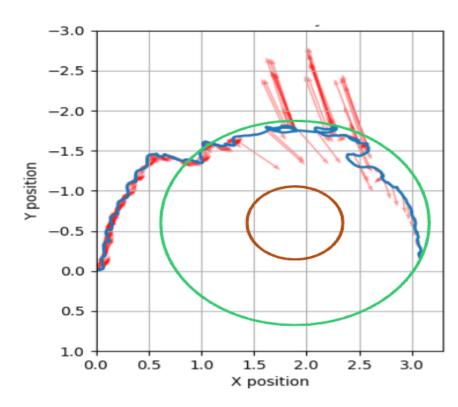
Forward motion prioritized:
 Vx_ reduced more than Vy due to frontal obstacle bias

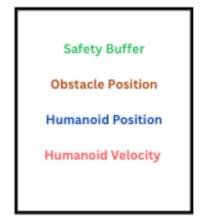
$$v_x = x[0] \cdot 0.05, \quad v_y = x[1] \cdot 0.4$$



Single Obstacle Simulation vs Real

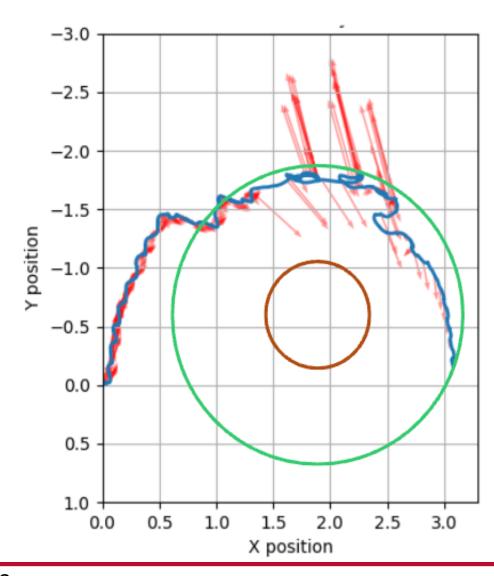






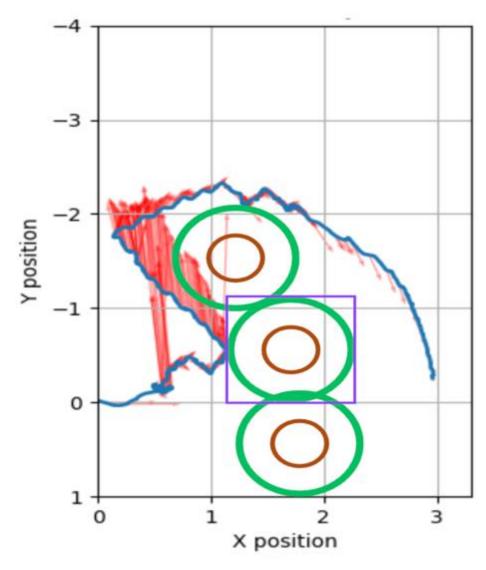


Single Obstacle



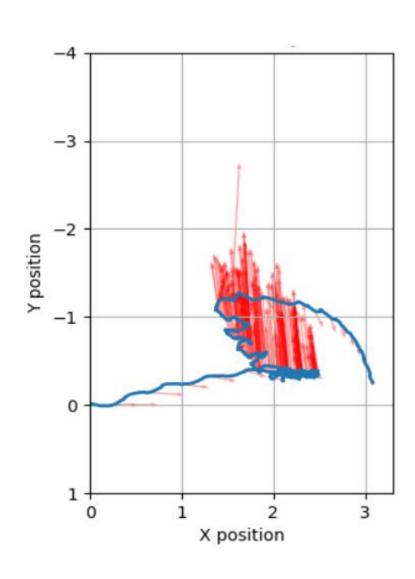


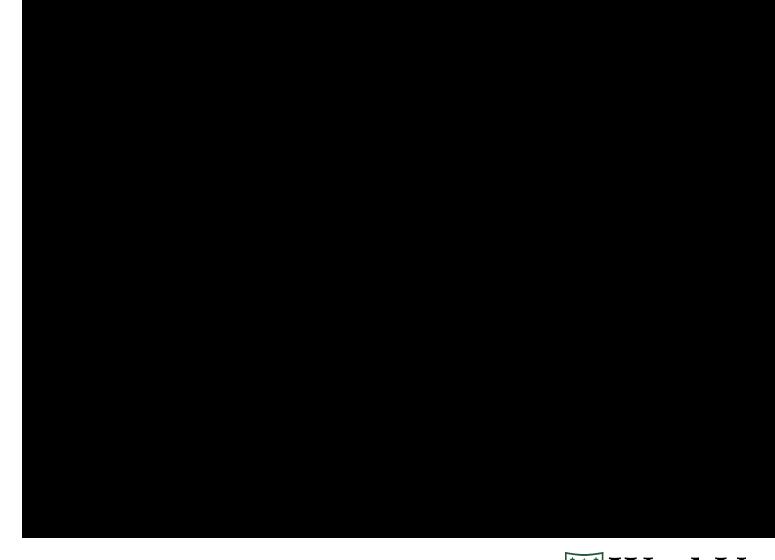
Wall of Obstacles





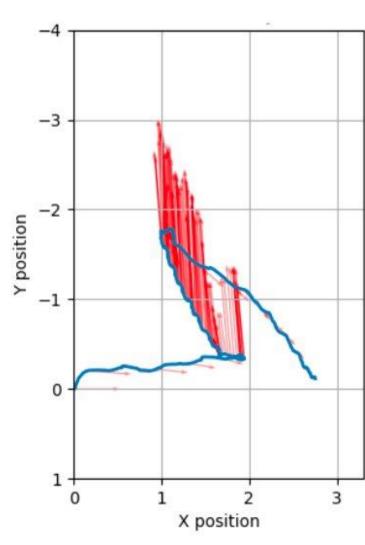
Moving Obstacle on Goal Point

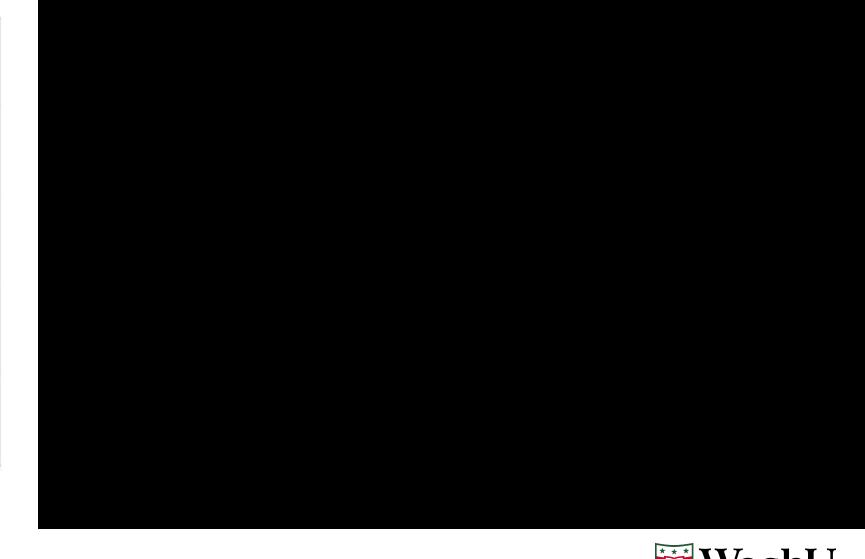






Approaching Moving Obstacle







Final Remarks

- Controller enables safe, convergent behavior on the G1 Humanoid
- Successfully avoids both static and dynamic obstacles without path planning
- Failures were not due to control formulation—but sensor and hardware limitations
- Main issues: LiDAR blind spots and odometry drift
- QP controller reacts correctly when obstacles re-enter field of view





Contributions

1/10 Scale Car

Open Loop Control

- Create Perception Pipeline
- Position and SA PID Controller
- Static & Dynamic CBF/PID QP Controller
- Multiple Obstacle CBF/PID QP Controller

<u>G1 Humanoid</u>

- Open Loop Control
- Create Perception Pipeline
- Position and SA PID Controller (Unicycle Dynamics)
- o Position PID Controller
- o Static & Dynamic CBF/CLF QP Controller
- Multiple Obstacle CBF/CLF QP Controller

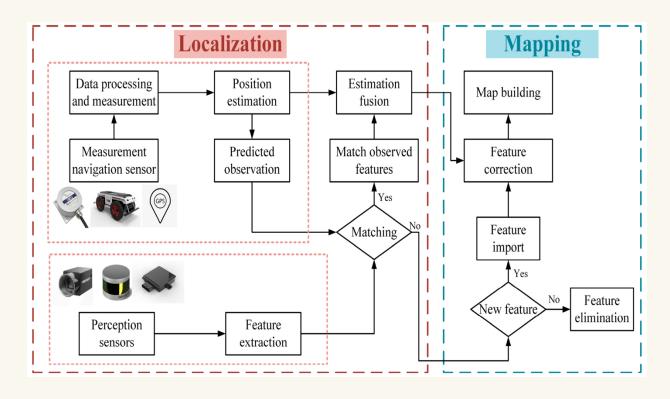


Future Work



Future Work

- Increased performance testing
- Implement SLAM Sensor Fusion
- Improve shape wrapping to reduce obstacle overestimation
- Adapt CBF/CLF to unicycle dynamics
- Extend CBF with alignment-based term:



SLAM Based Sensor Fusion Pipeline

$$b(x, y, \theta) = (x - x_o)^2 + (y - y_o)^2 + \theta^2 - R^2$$



Acknowledgments

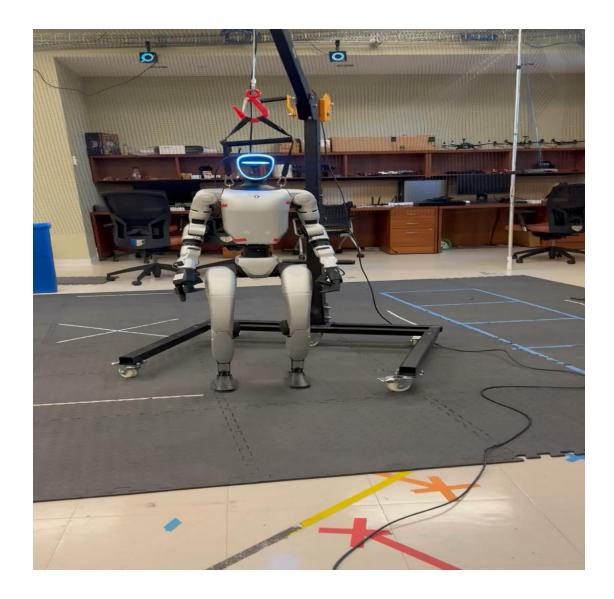


Andrew Clark	Yiannis Kantaros	ShiNung Ching
Jash Narwani	Michal Zemanek	HongChao Zhang
Dzenan Zecevic	Mario Rodriguez	Ziyi Peng





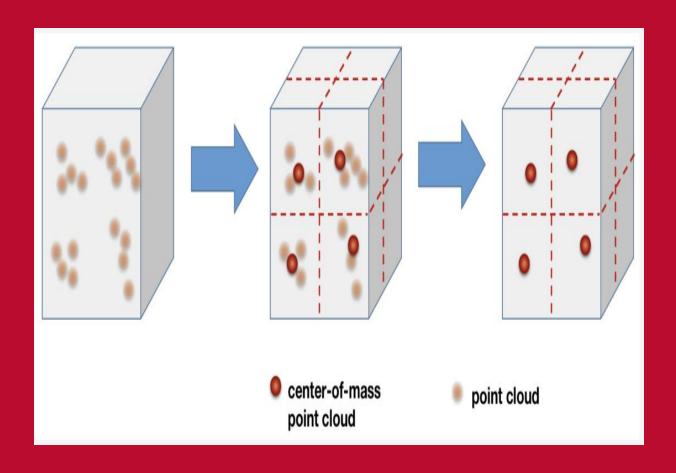
Thank You!

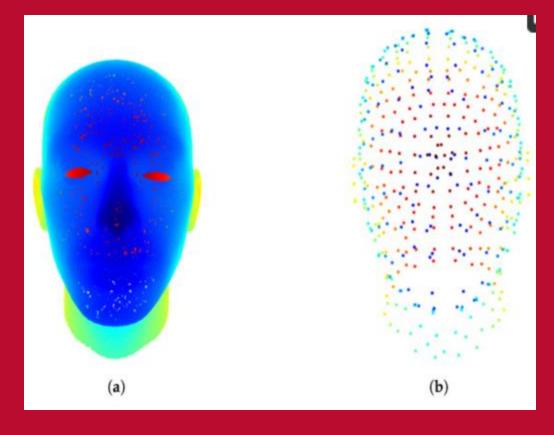






Voxel Filter







CBF Constraint Single Integrator Dynamics

$$2(p_x - x_{\text{obs}})u_x + 2(p_y - y_{\text{obs}})u_y \ge 0$$

