A hundred times every day I remind myself that my inner and outer life are based on the labors of other men, living and dead, and that I must exert myself in order to give in the same measure as I have received and am still receiving...

Kumaraguru Sivasankaran

MS in Aeronautics and Astronautics Engineering
Candidate for Controls Engineer

KITTYHAWK

ANNA UNIVERSITY
PROGRESS THROUGH KNOWLEDGE

PURDUE UNIVERSITY

Slides at https://ksivasan.com/files/presentation.pdf

DAIMLER

VOLVO

Journey so far..

Grounding work

Modern Control theory

- Linear systems
- Non linear Systems
- Distributed Network Control
- Optimal Control and Estimation
- Linear Algebra

Computational Science

- Optimization
- Computer Vision
- Parallel Computing
- Machine learning
- Deep learning

Applied Statistics

- Statistical methods
- Probability
- Design of Experiments
- Regression Analysis
- Computational Statistics I

Control design:
- PID controller
- LQR controller
- Model predictive Controller
- Sliding mode controllers
- High Gain observers
- Hybrid system control

Trajectory Optimization:
- Dynamic Programming
- Calculus of Variations

Sensor fusion / Estimation:
- Kalman filtering, EKF, UKF
- Least Squares Minimization
- Levenberg Marquardt optimization
- Sampling methods
- Monte Carlo simulations
- 3D reconstruction from 2D images
- Object detection and localization
- Camera calibration

System modeling:
- Physics based modeling
- Markov Decision Process
- Partially Observable Markov Decision Process
- Deep Neural Networks
- Gaussian Process models

My mentors @Purdue

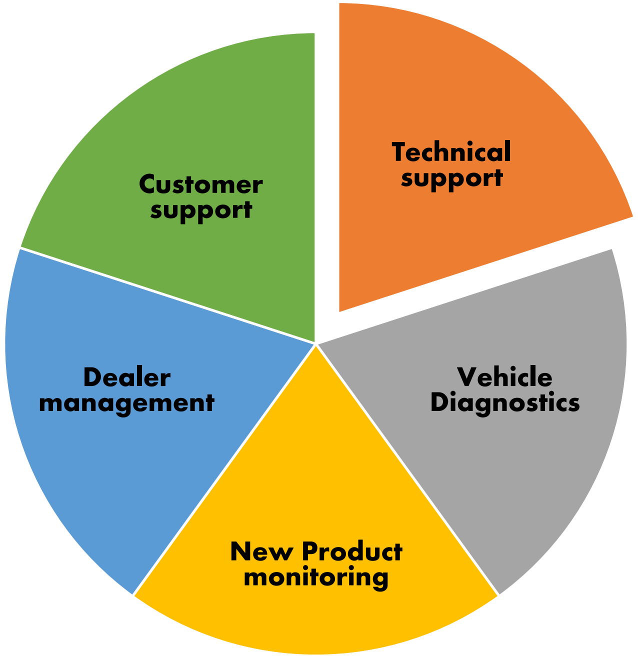
With Dr. Xiao Wang, Professor, Dept. of Statistics
Work: Reinforcement learning

With Dr. Martin Corless, Professor, Dynamics and Controls, Aeronautics and Astronautics Engineering
Work: Consensus algorithms

With Dr. Jan E Mansson, Distinguished Professor of Materials and Chemical Engineering and AAE (by Courtesy)
Work: Technical Cost Modeling

Life at Daimler (2014-16)

- Experienced with the lifecycle of a truck from production to full operation and finally to resale / scrap.
- Familiar with Maintenance cycle, Product failures, Failure analysis and Total Cost of Ownership calculations (TCO).
- Offered technical support when a trained technician was unable to troubleshoot a vehicle off road.
- Ensured customer satisfaction in terms of overall Aftersales service support to West Gujarat, India
- Collaborated with people at different levels
  - Technician, Dealer manager, Dealer Principal, Customer
  - Regional manager, Technical services, Warranty, PMG, VP
- Led field trials for establishing performance and responsible for New Product Monitoring
- Appreciated for quick learning, taking up responsibility and delivering with consistently high KPI in the region



Aftersales Service Manager

Coop at Volvo (2017)

- Verification and Validation of control systems for Production Vehicle Evaluation (PVE)

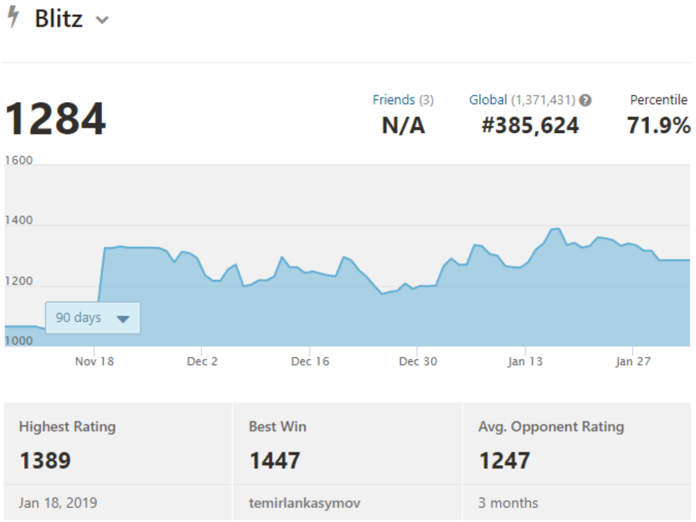
- Over 500 miles of road testing per week

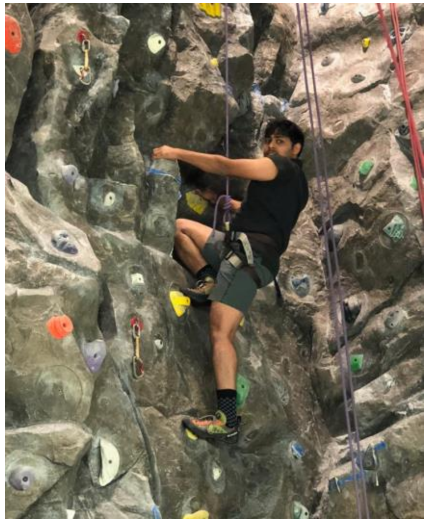
- Involved Data collection, Analysis, Failure reporting and documentation

- More than 50 tests performed in a span of 4 months (Aug- Dec)

- Familiar with use of functional documentation for evaluation and troubleshooting

Hobbies

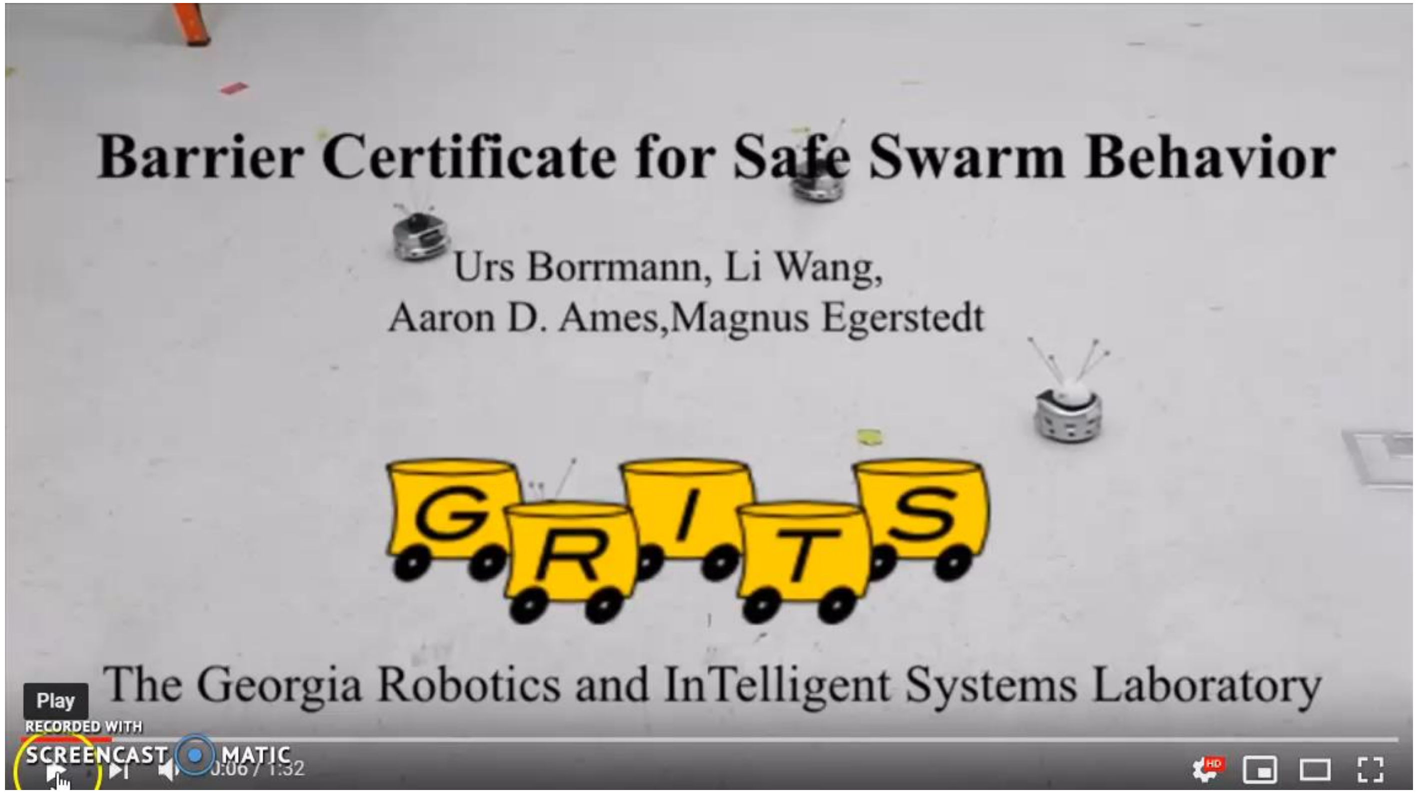




And more..

Decentralized controller for Multiagent systems – A motivation

Wanis Kabbaj: What a driverless world could look like



Where do we stand now?

Safety barrier Certificate: A review

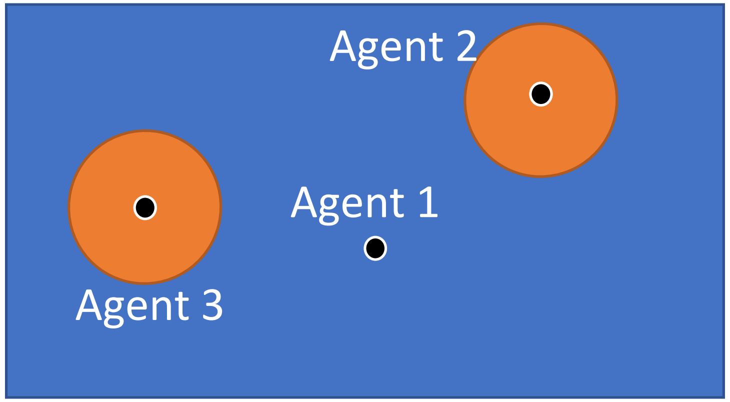
Non-linear system: $\dot{x} = f(x) + g(x)u$

Control invariance set:

$$C = \{x \in R^n : h(x) \geq 0\}$$

$$\partial C = \{x \in R^n : h(x) = 0\}$$

$$Int\ (C) = \{x \in R^n : h(x) > 0\}$$



Barrier function: $\inf_{x \in Int(C)} B(x) \geq 0 \quad \lim_{x \to \partial C} B(x) = \infty$

Barrier function dynamics: $\dot{B} \leq \frac{\gamma}{B}$ Stronger condition: $\dot{B} \leq 0$

Control Barrier function:

$$\inf_{u \in U} \left[L_f B(x) + L_g B(x) u - \frac{\gamma}{B(x)} \right] \leq 0$$

$$K_{cbf}(x) = \{u \in U : L_f B(x) + L_g B(x) u - \frac{\gamma}{B(x)} \leq 0\}$$

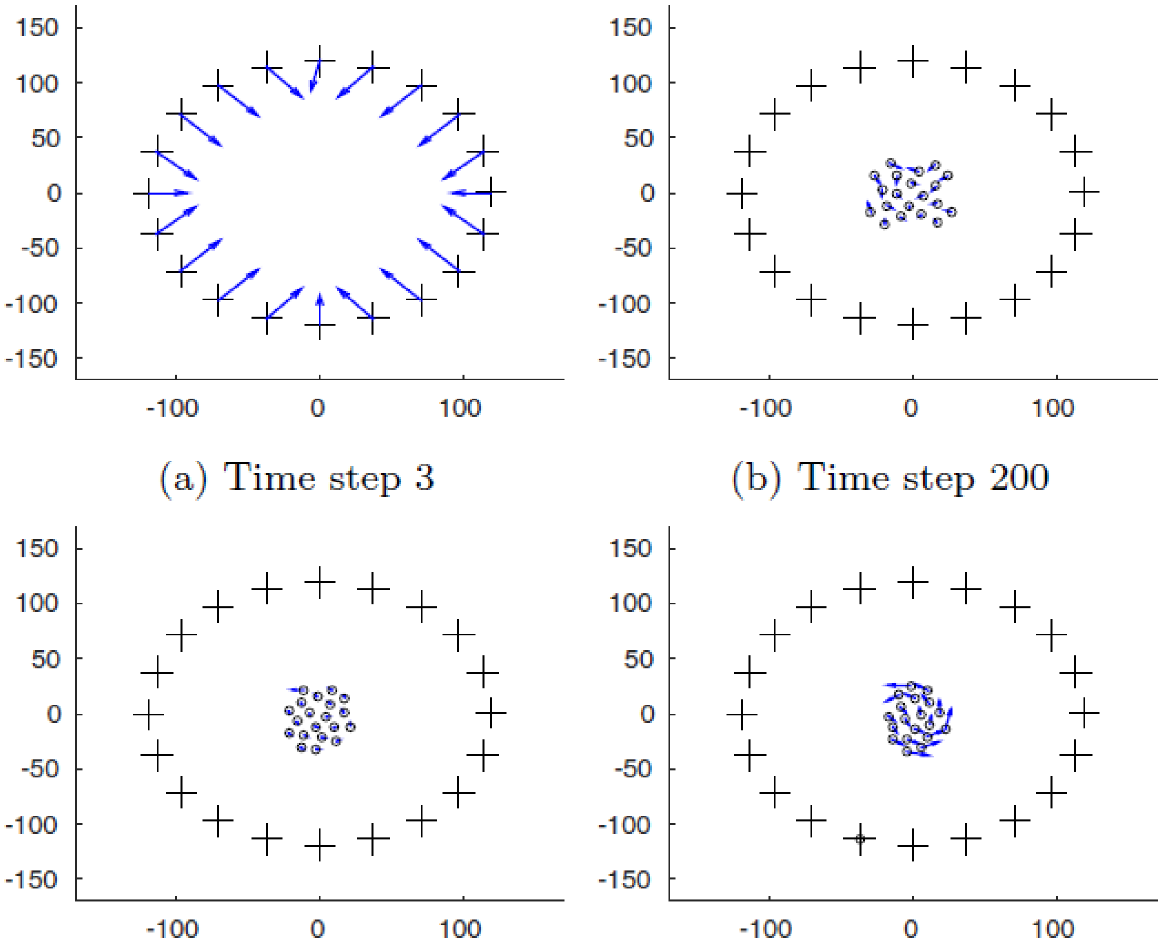
Review (contd.)

Solution: controller based on Quadratic programming:

$$u^* = argmin_u\, J(u) = \sum_i ||u_i - \hat{u}_i||^2$$

$$s.t.\quad A_{ij}u \leq b_{ij}, \qquad \forall i \neq j$$

$$||u_i||_\infty \leq a_{max}, \qquad \forall i \in M$$



(a) Time step 3 (b) Time step 200

(c) Time step 600 (d) Time step 850

Problems with this approach:

- Sluggish overall
- Conservative behavior in decentralized case
- Deadlocks due to infeasible optimization solutions

Reference: Borrmann, U., Wang, L., Ames, A. D. & Egerstedt, M. (2015). Control Barrier Certificates for Safe Swarm Behavior.. In M. Egerstedt & Y. Wardi (eds.), ADHS (p./pp. 68-73), : Elsevier

Problem setup and approach

Double integrator dynamics:

$$\begin{bmatrix}\dot{p}_i \\ \dot{v}_i\end{bmatrix} = \begin{bmatrix}0 & I_{2*2} \\ 0 & 0\end{bmatrix}\begin{bmatrix}p_i \\ v_i\end{bmatrix} + \begin{bmatrix}0 \\ I_{2*2}\end{bmatrix} u_i$$

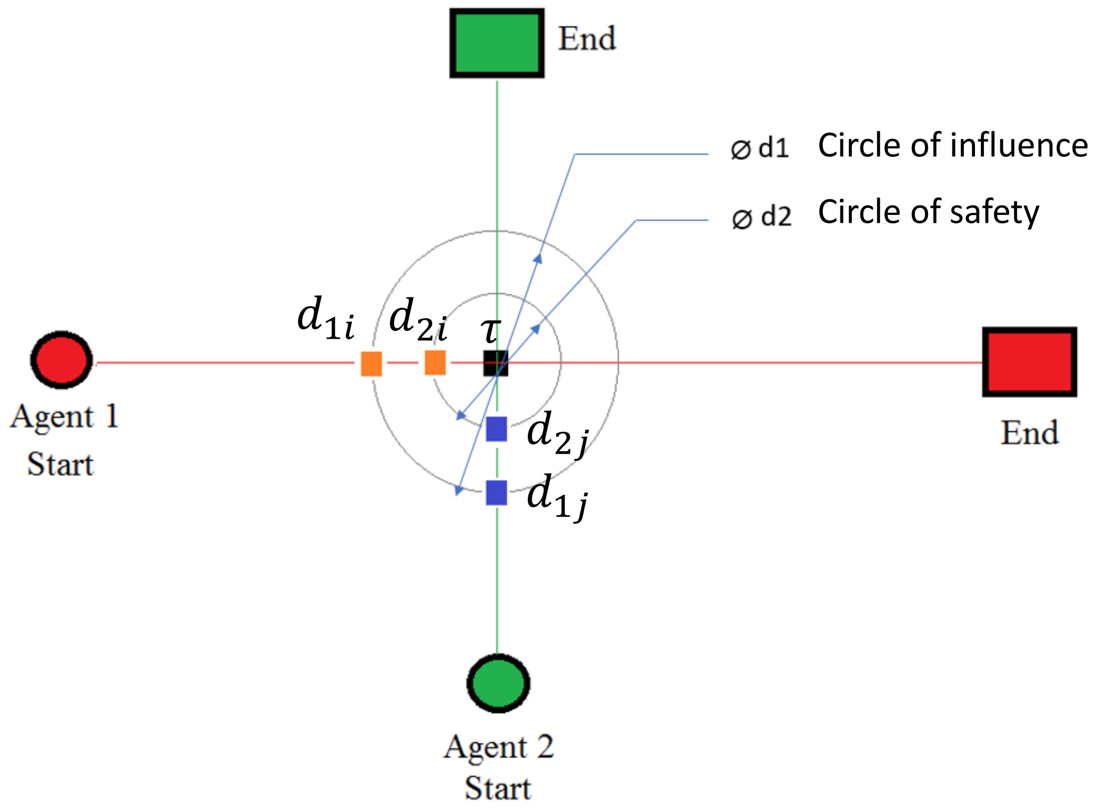
$p_i \in R^2, v_i \in R^2, u_i \in R^2$ are position, velocity and acceleration of agent i

Reference point (final):

$$r_i = \begin{bmatrix}r_{ix} \\ r_{iy}\end{bmatrix}$$

Nominal controller to achieve end goal with zero velocity:

$$u_i = -k_1(p_i - r_i) - k_2 v_i$$



Reference: Mou, S., Cao, M., & Morse, A. S. (2015). Target-point formation control. Automatica, 61, 113-118.

Target point control

Position vectors:

$$A_i = \begin{bmatrix} p_{xi} \\ p_{yi} \end{bmatrix} + \mu \begin{bmatrix} p_{xi} - r_{xi} \\ p_{yi} - r_{yi} \end{bmatrix} \qquad A_j = \begin{bmatrix} p_{xj} \\ p_{yj} \end{bmatrix} + t \begin{bmatrix} p_{xj} - r_{xj} \\ p_{yj} - r_{yj} \end{bmatrix}$$

At point of intersection: $A_i = A_j$

Solve for intersection point:

$$\begin{bmatrix} \mu \\ t \end{bmatrix} = \begin{bmatrix} p_{xi} - r_{xi} & r_{xj} - p_{xj} \\ p_{yi} - r_{yi} & r_{yj} - p_{yj} \end{bmatrix}^{-1} \begin{bmatrix} p_{xj} - p_{xi} \\ p_{yj} - p_{yi} \end{bmatrix}$$

$$\tau = \begin{bmatrix} p_{xi} \\ p_{yi} \end{bmatrix} + \mu^* \begin{bmatrix} p_{xi} - r_{xi} \\ p_{yi} - r_{yi} \end{bmatrix} = \begin{bmatrix} p_{xj} \\ p_{yj} \end{bmatrix} + t^* \begin{bmatrix} p_{xj} - r_{xj} \\ p_{yj} - r_{yj} \end{bmatrix}$$

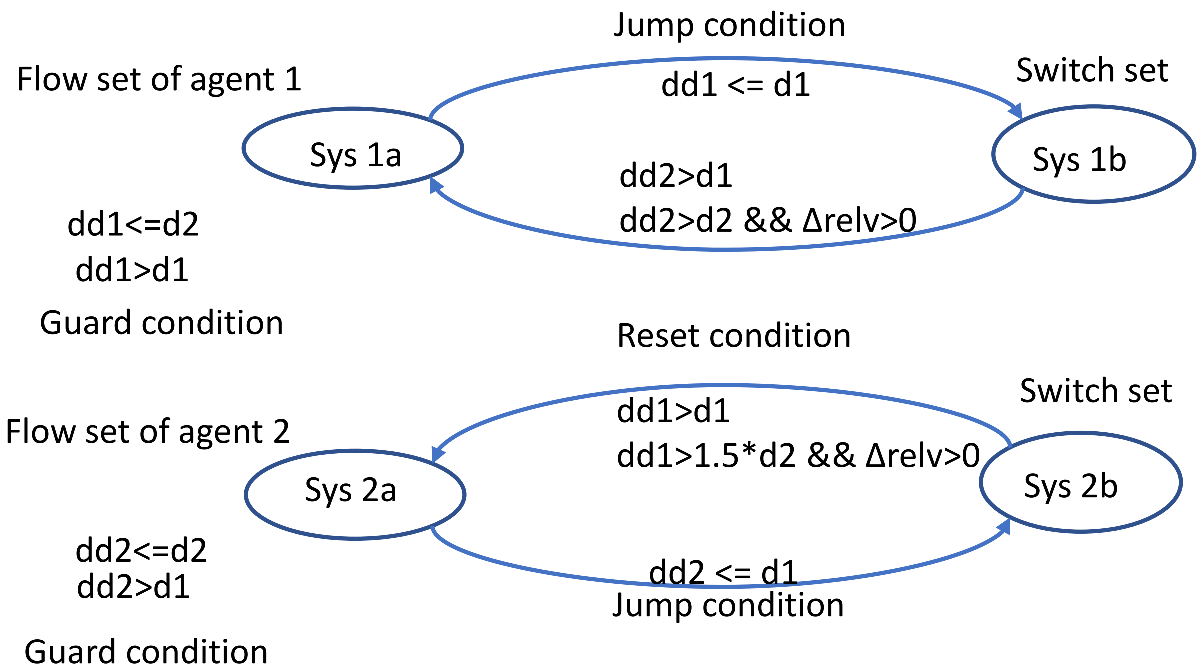
Target Points:

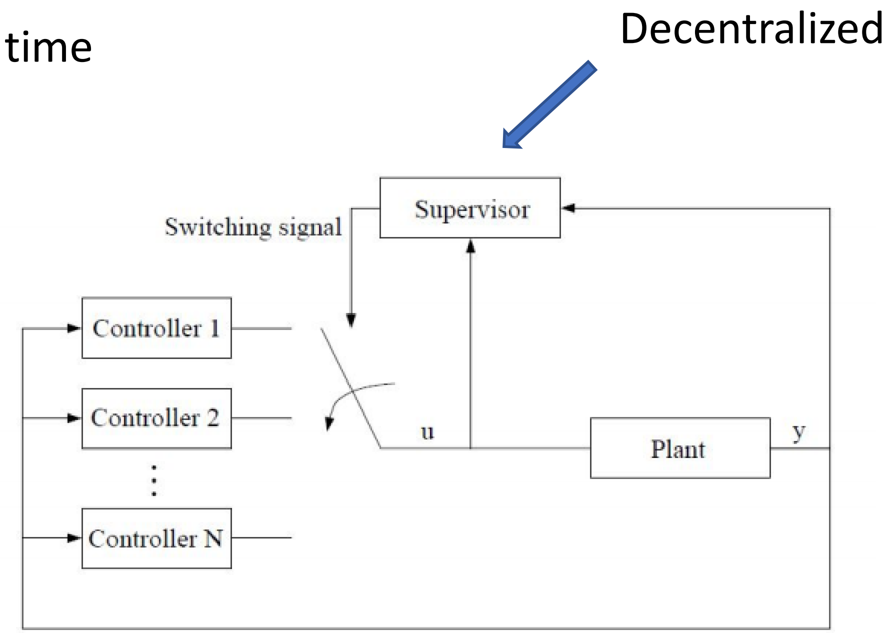
$$d_{1i} = p_i - \frac{\left\| \tau - p_i \right\| - d_1}{\|\tau - p_i\|} (\tau - p_i) \qquad d_{2i} = p_i - \frac{\left\| \tau - p_i \right\| - d_2}{\|\tau - p_i\|} (\tau - p_i)$$

$$d_{1j} = p_j - \frac{\left\| \tau - p_j \right\| - d_1}{\left\|\tau - p_j\right\|} (\tau - p_j) \qquad d_{2j} = p_j - \frac{\left\| \tau - p_j \right\| - d_2}{\left\|\tau - p_j\right\|} (\tau - p_j)$$

Hybrid distributed control design

Flow set : Continuous ODE dynamic system where agent spends most time
Switch set: Alternate system dynamics
Guard condition: Keeps system in flow set
Jump condition: Discrete transitions from flow set to switch set
Reset condition: Returns to flow set





Nominal $$u_i = -k_1(p_i - r_i) - k_2 v_i$$

Switched $$u_i = -k_1(p_i - d_{2i}) - k_2 v_i$$

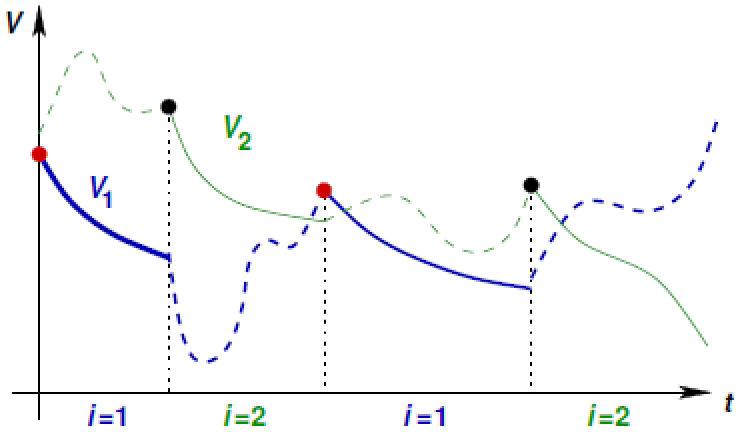
Analysis and Results

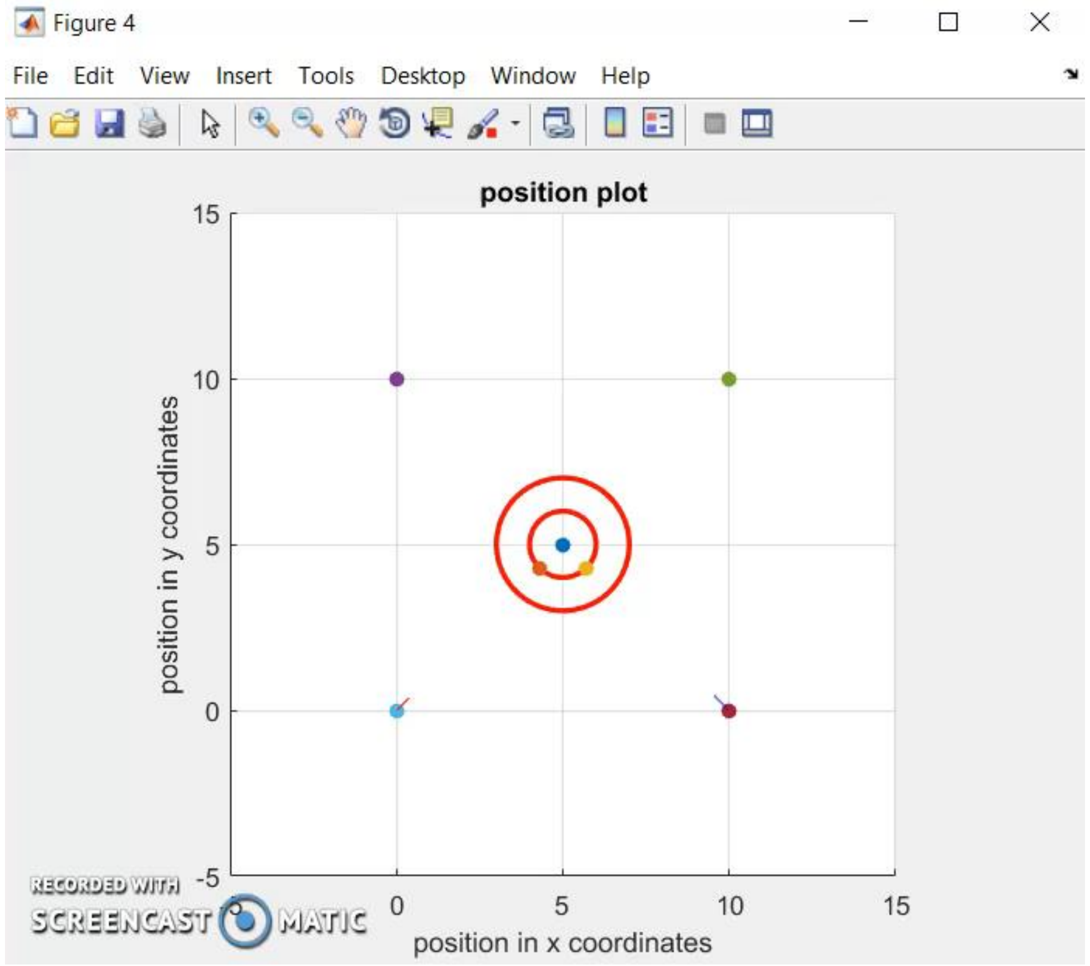
Theorem:

Consider switched system with all sub models $\dot{x} = f_i(x)$ as Globally asymptotically stable with corresponding Lyapunov function V_i.

Suppose for every pair of switching times $(t_k, t_l), t < l$ with $\sigma(t_k) = \sigma(t_l) = i$ and $\sigma(t_m) \neq i$ for $t_k < t_m < t_l$, we have

$V_i(x(t_l)) - V_i(x(t_k)) \leq -\rho(||x(t_k)||) < 0$, then the switched system is GAS

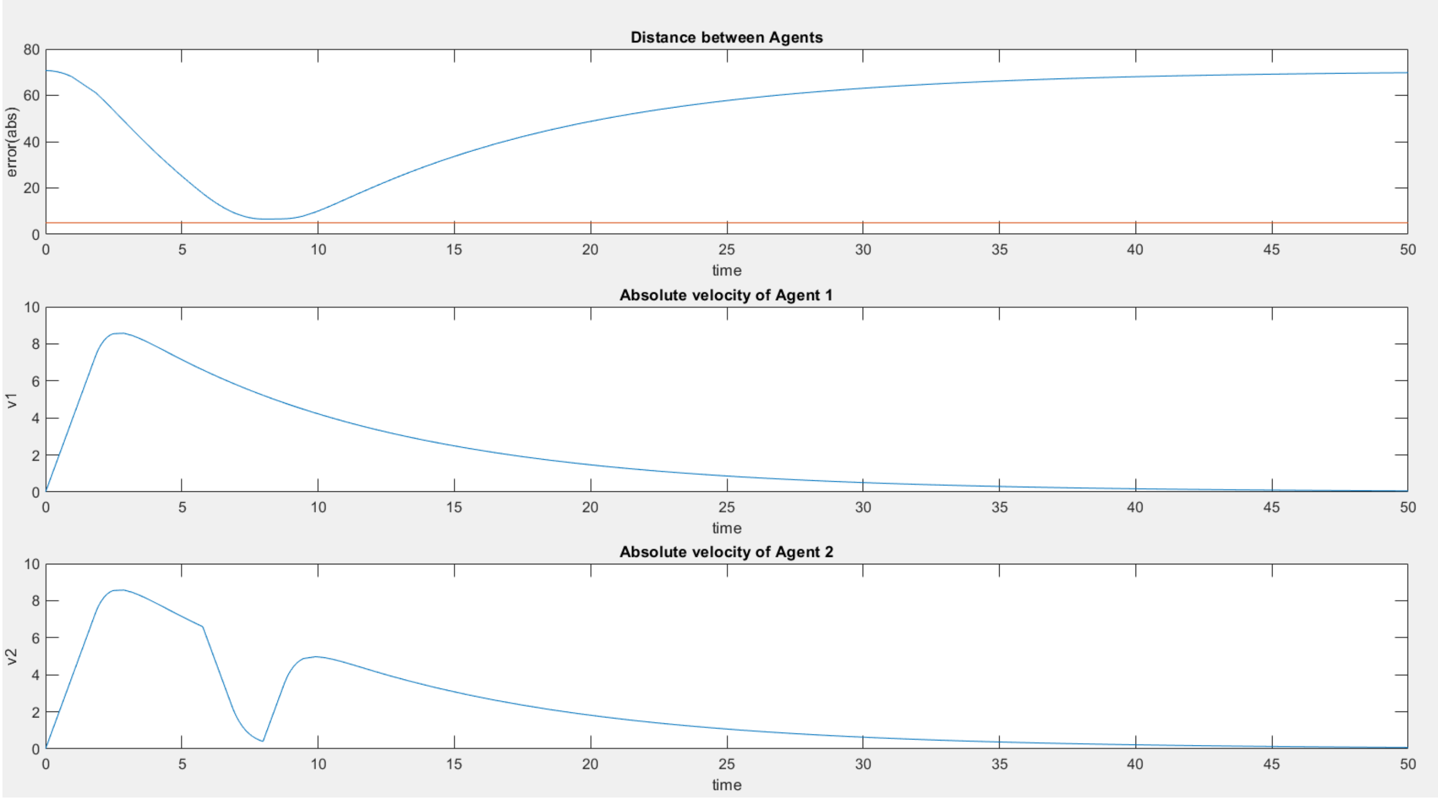


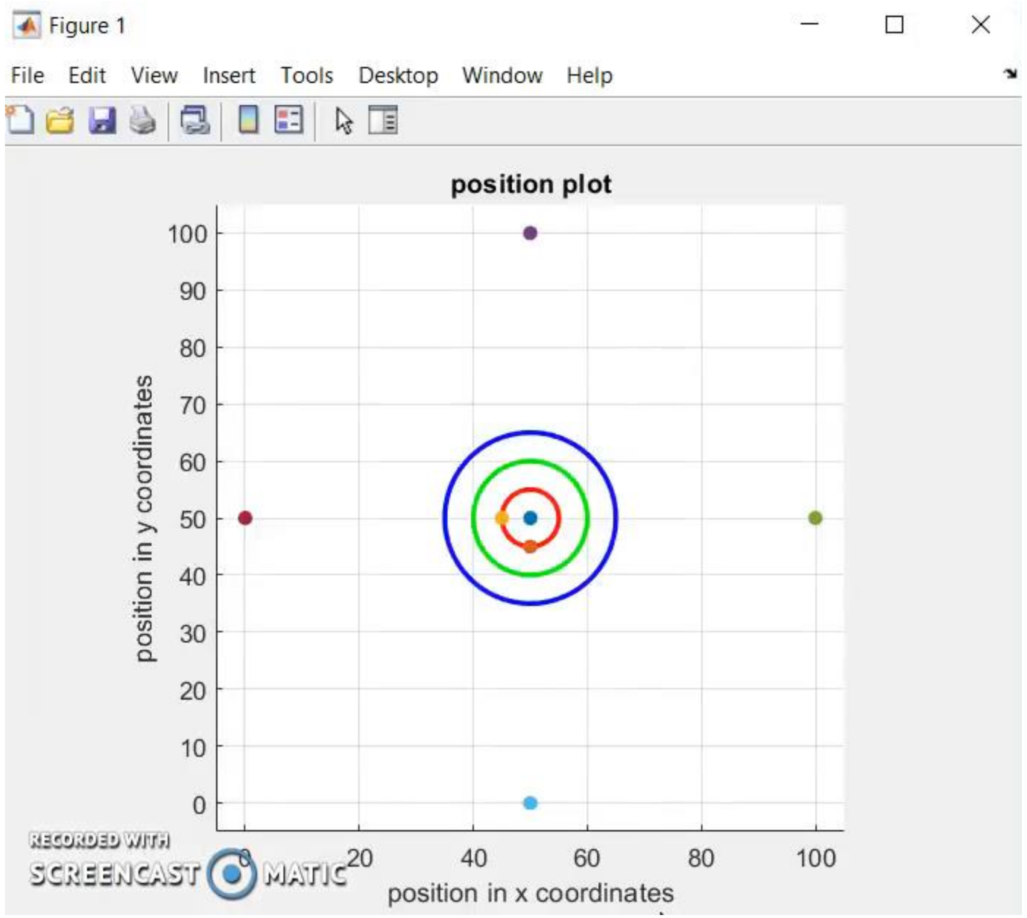


Agents having different max speed

Reference: Branicky, M. S. (1998). Multiple Lyapunov functions and other analysis tools for switched and hybrid systems. IEEE Transactions on automatic control, 43(4), 475-482.

Results:





Agents having same max speed

Advantages

- Combination of two ideas – target point control and control barrier certificates (switching).
- Simpler than Quadratic programming controller.
- Eliminates unwanted deviation from path.
- Fast response and less use of computation.

Disadvantages:

- Assumes that the path travelled by both agents are always in straight lines.
- Requires additional control algorithm for scaling to multiple agents (e.g. consensus based ranking for resolving deadlocks)
- Symmetric cases are not handled.

High-gain observers

Non-linear system $\dot{x}_1 = x_2$

$\dot{x}_2 = \phi(x, u, w)$

Measurement $y = x_1$

Control Objective *To stabilize the origin x=0*

u = $\gamma(x, w)$

Observer $\dot{\hat{x}}_1 = \hat{x}_2 + h_1(y - \hat{x}_1)$

$\dot{\hat{x}}_2 = \phi_0(\hat{x}, u) + h_2(y - \hat{x}_1)$

Error Dynamics $\dot{\tilde{x}}_1 = -h_1\tilde{x}_1 + \tilde{x}_2$

$\dot{\tilde{x}}_2 = -h_2\tilde{x}_1 + \delta(x, \tilde{x}, w)$

$\tilde{x}_1 = x_1 - \hat{x}_1$

$\tilde{x}_2 = x_2 - \hat{x}_2$

$\delta = \phi(x, \gamma(\hat{x}), w) - \phi_0(\hat{x}, \gamma(\hat{x}))$

Reference: Khalil, H. K., & Praly, L. (2014). High-gain observers in nonlinear feedback control. International Journal of Robust and Nonlinear Control.

Lecture series: Forum on Robotics & Control Engineering http://force.eng.usf.edu/

Contd.

Change of variables

$$h_1 = \frac{\alpha_1}{\epsilon} \qquad h_2 = \frac{\alpha_2}{\epsilon^2}$$

$$\eta_1 = \frac{\tilde{x}_1}{\epsilon} \qquad \eta_2 = \tilde{x}_2$$

New Dynamics

$$\epsilon\,\dot{\eta}_1 = -\alpha_1\eta_1 + \eta_2$$

$$\epsilon\,\dot{\eta}_2 = -\alpha_2\eta_1 + \epsilon\,\delta$$

Peaking phenomenon

$$\eta_1(0) = \frac{\tilde{x}_1(0)}{\epsilon} = \frac{x_1(0) - \hat{x}_1(0)}{\epsilon}$$

$$\eta_1(0) = O\left(\frac{1}{\epsilon}\right)$$

Transient response could be impulsive in short time and could destabilize the system

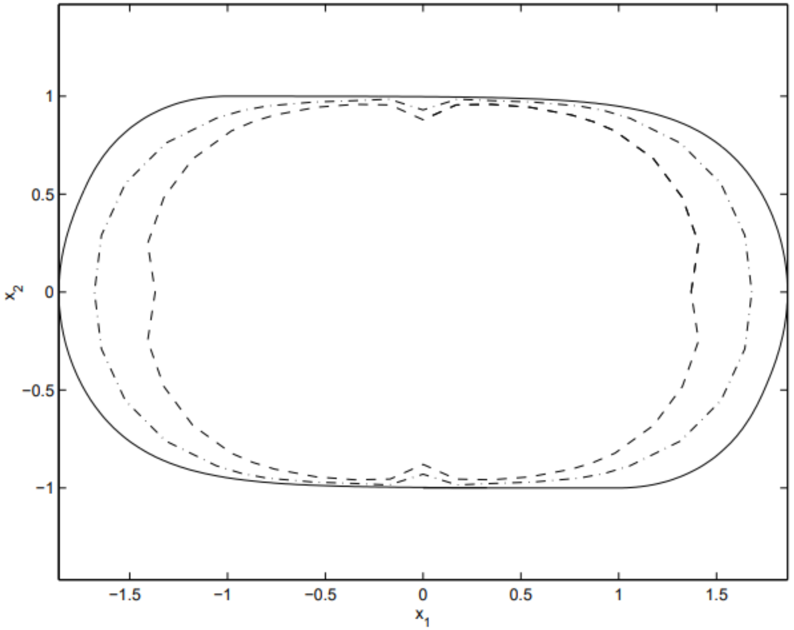
Solution: Control saturation

Advantages

- Asymptotic stability of origin as ϵ tends to zero
- Recovers region of attraction
- Recovers state trajectories

Disadvantages

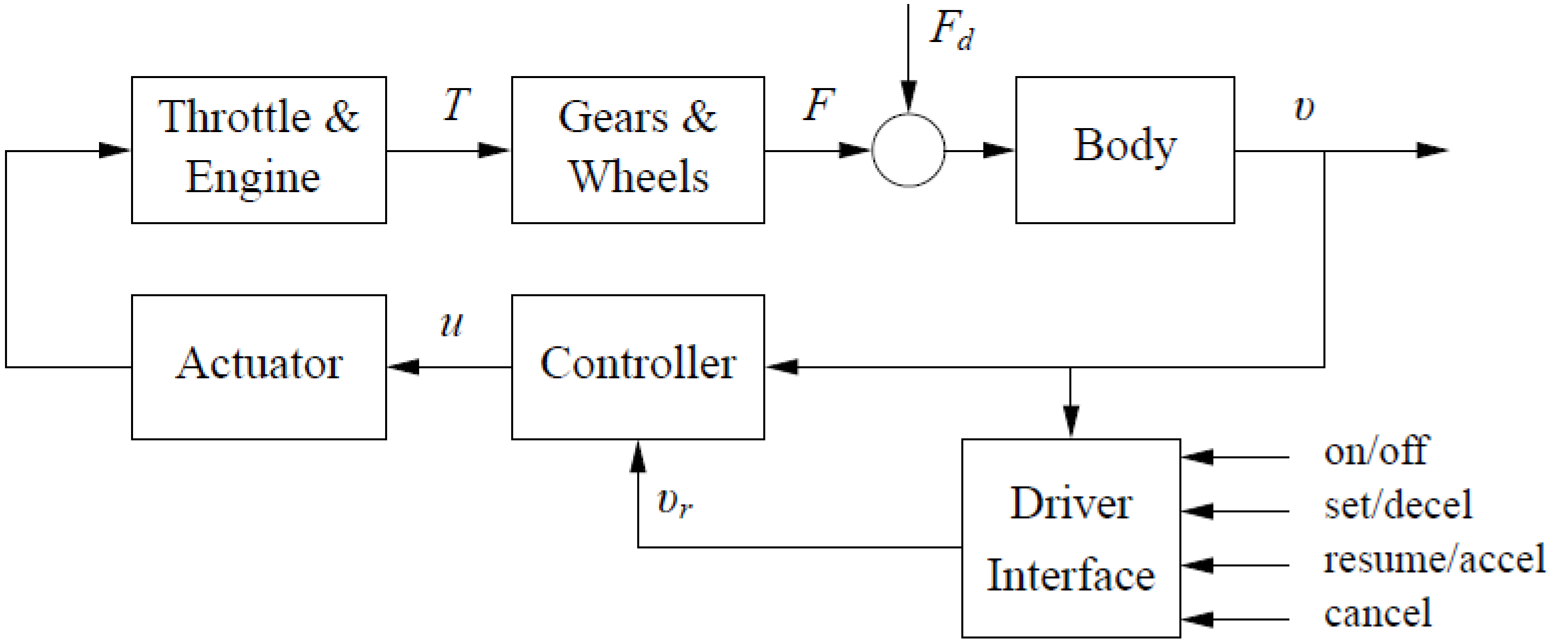
- High gain increases error due to noisy measurements
- Faster response at transient but poor steady-state performance
- No guarantee of asymptotic stability to origin. Converges within an error of ϵ



Region of attraction under state feedback and output feedback for different values of ϵ

Solution: Non-linear gain scheduling – high gains during transient phase and lower gain at steady state
Alternate: Sliding mode controller

Extended High Gain observers for output feedback control of Non-linear systems



Motivating example: Adaptive Cruise control

System dynamics

Newton's law: $$m\frac{dv}{dt} = F_{engine} - F_{drag}$$

Engine rpm: $$\omega = \frac{n}{r}\, v =: \alpha_n v$$

$r = \text{wheel radius},\ n = gear\ ratio,$
$v = linear\ velocity$

Typical values
$\alpha_1 = 40$
$\alpha_2 = 25$
$\alpha_3 = 16$
$\alpha_4 = 12$
$\alpha_5 = 10$

Force due to engine: $$F_{engine} = \frac{nu}{r}\, T(\omega) = \alpha_n u T(\alpha_n v)$$

$u = Control\ input\ (rate\ of\ fuel\ injection)$

$$T(\omega) = T_m(1 - \beta\left(\frac{\omega}{\omega_m} - 1\right)^2)$$

$T_m = Max\ torque = 190\ Nm$
$\omega_m = Max\ Engine\ rpm = 420\ rads^{-1}$
$\beta = 0.4$

Force due to friction: $$F_r = mgC_r\ sign(v)$$

$m = mass\ of\ car, g = gravity,$
$C_r = 0.01 = Coefficient\ of\ Rolling\ friction$

Aerodynamic drag: $$F_a = \frac{1}{2}\rho C_d A v^2$$

$\rho = Density\ of\ air = 1.3\frac{kg}{m^3}\ , C_d = Drag\ coefficient = 0.32$
$A = Frontal\ area\ of\ car = 2.4m^2$

Reference: Feedback Systems, K. J. Astrom & R. Murray

Contd.

Weight component: $F_w = mg\sin(\theta)$ $\qquad \theta = slope\ of\ road$

Total forces: $$m\frac{dv}{dt} = \alpha_n uT(\alpha_n v) - mgC_r\ sign(v) - \frac{1}{2}\rho C_d Av^2 - mg\sin(\theta)$$

PID Controller: $$u(t) = k_p e(t) + k_i \int_0^t e(\tau)\,d\tau + k_d \dot{e}(t)$$

Perfect state information available $\Rightarrow$ *State feedback controller works*

Unmodelled dynamics/ non-linearities always exists.
Finding perfect model is a challenging task than designing controller

Extended High-Gain Observer

Non-linear system

$$\dot{x}_1 = x_2$$
$$\dot{x}_2 = a(x,w) + b(x,w)u$$

Measurement

$$y = x_1$$

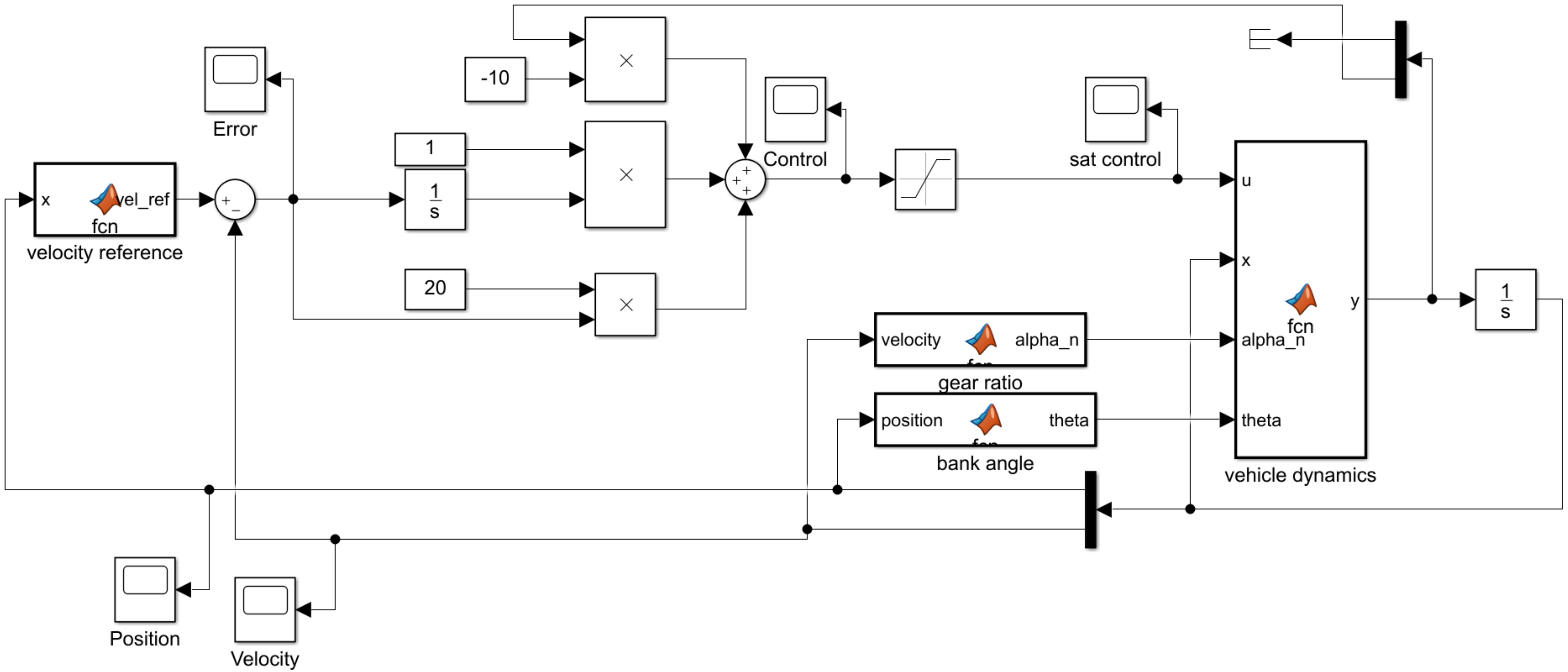
Extended Dynamics

$$\dot{x}_1 = x_2$$
$$\dot{x}_2 = a_0(x) + b_0(x)u + \sigma \qquad \textit{where } \sigma = a(x,w) - a_0(x) + \big(b(x,w) - b_0(x)\big)u$$
$$\dot{\sigma} = \phi(x, w, \dot{w}, u, \dot{u})$$
$$y = x_1$$

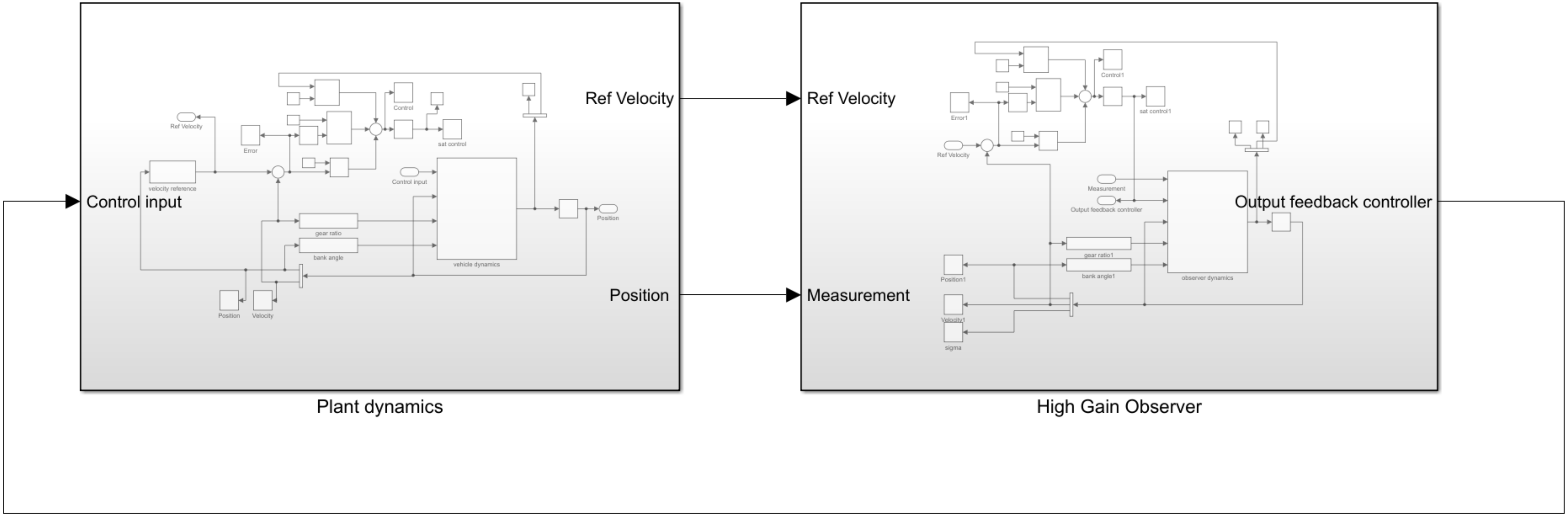
High-gain observer

$$\dot{\hat{x}}_1 = \hat{x}_2 + \frac{\alpha_1}{\epsilon}(\mathrm{y} - \hat{\mathrm{x}}_1)$$
$$\dot{\hat{x}}_2 = a_0(\hat{x}) + b_0(\hat{x})u + \hat{\sigma} + \frac{\alpha_2}{\epsilon^2}(\mathrm{y} - \hat{\mathrm{x}}_1)$$
$$\dot{\hat{\sigma}} = \frac{\alpha_3}{\epsilon^3}(\mathrm{y} - \hat{\mathrm{x}}_1)$$

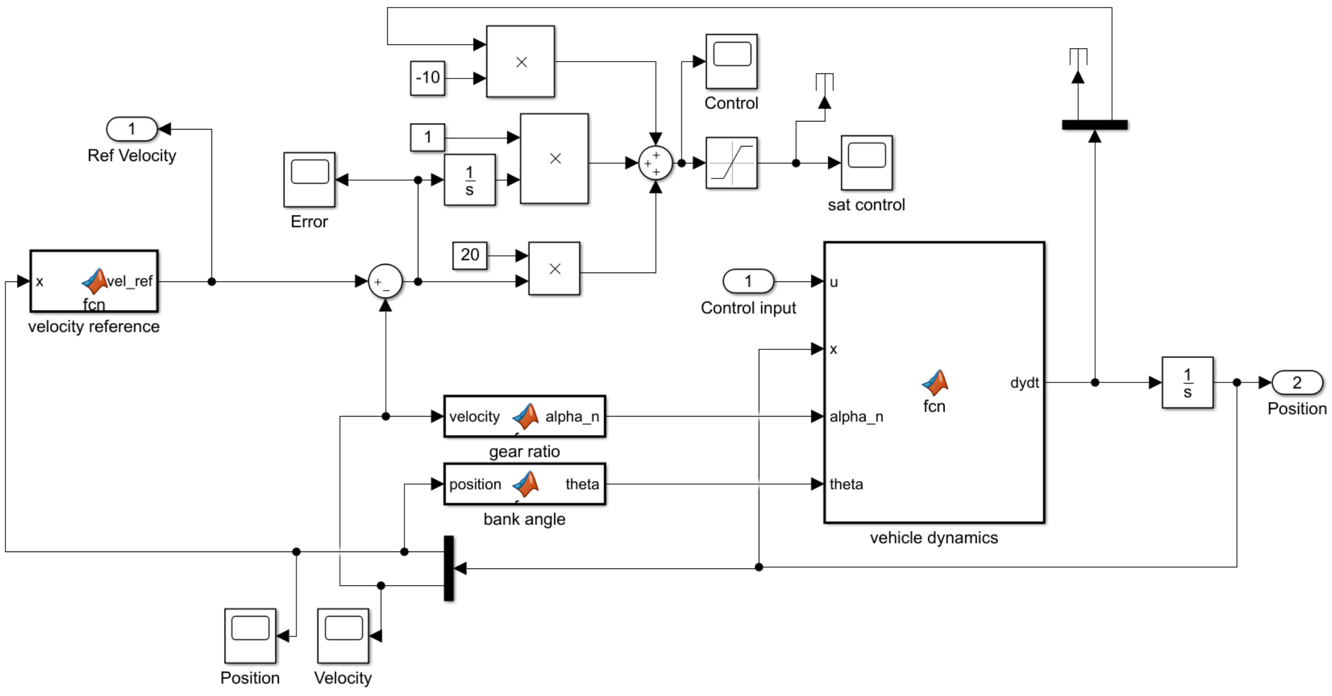
State feedback controller



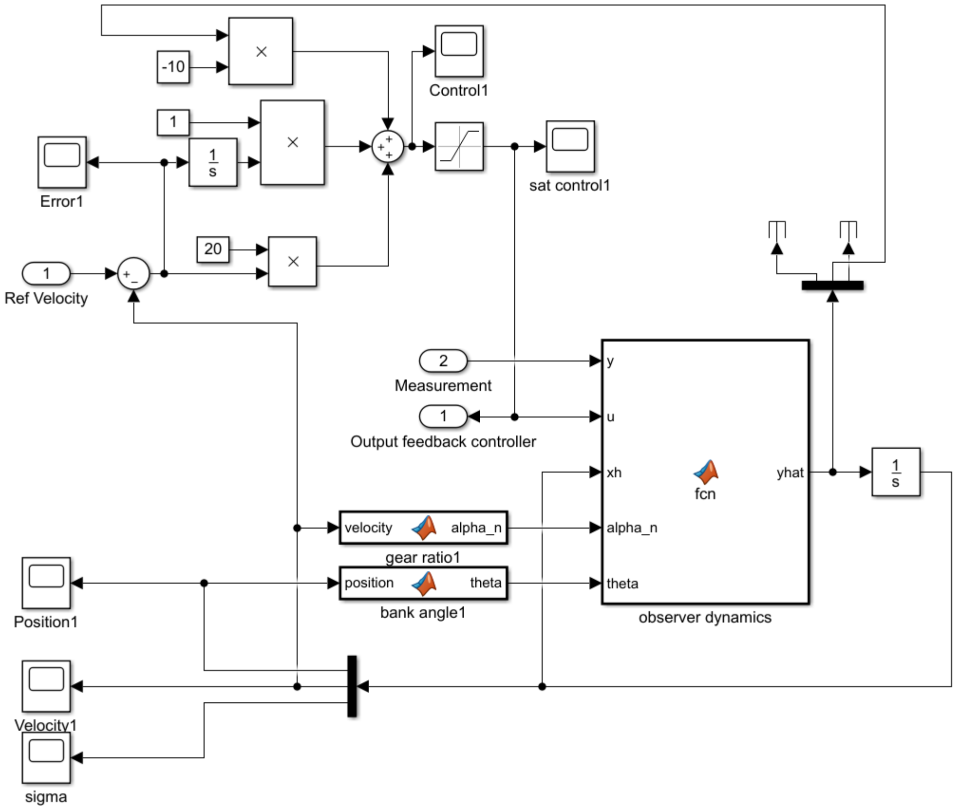
Output feedback controller



Simulation

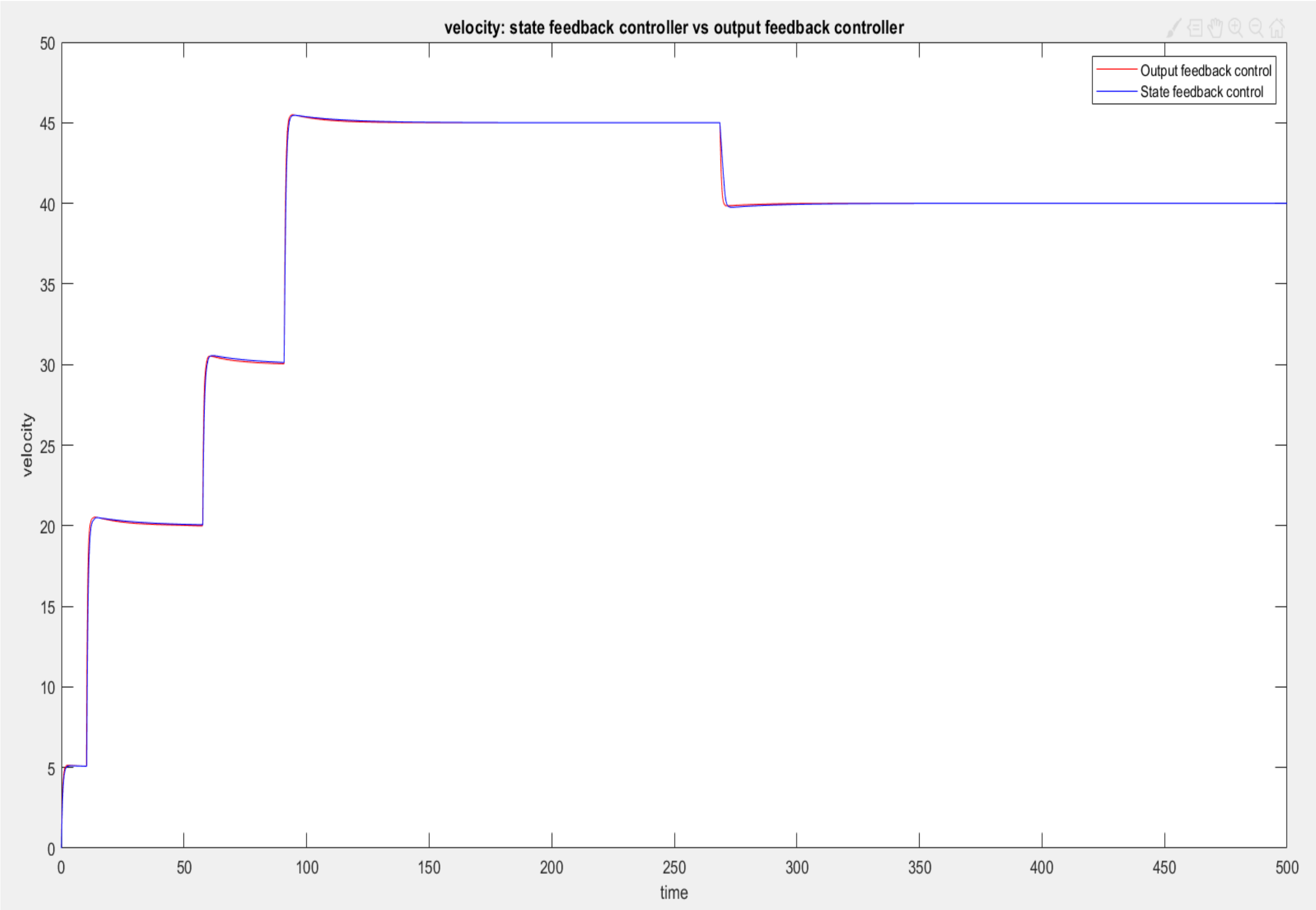


Plant dynamics



Observer dynamics

Results



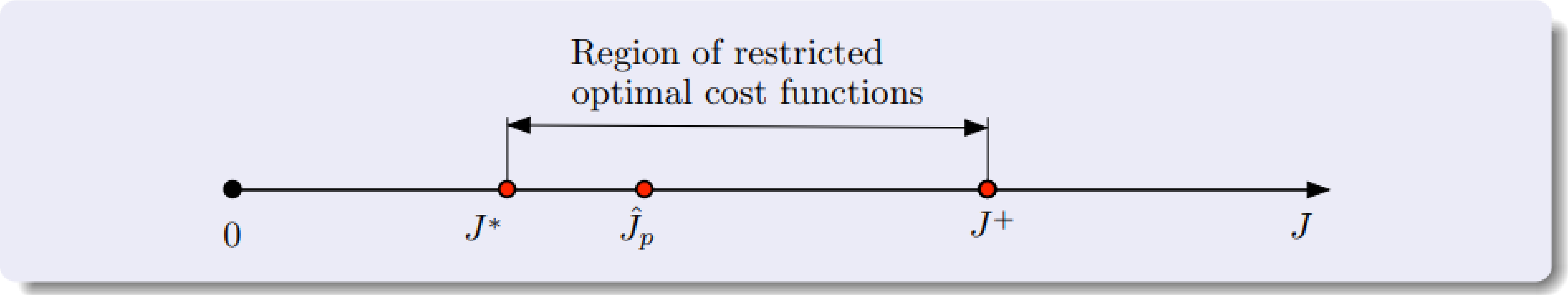
Parameters in Observer dynamics are modified to induce modeling inaccuracy.

For example: mass of the car was varied +/- 30% , frictional force set to zero, drag coefficient varied.

Yet, output feedback controller (using high gain observers) perform* at par with state feedback controller as seen here.

*Requires tuning gain, epsilon for higher modeling errors

Thank you



Optimality $\not\rightarrow$ Stability

$J(x) = \inf_{u \in U(x)} H(x, u, J)$