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

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

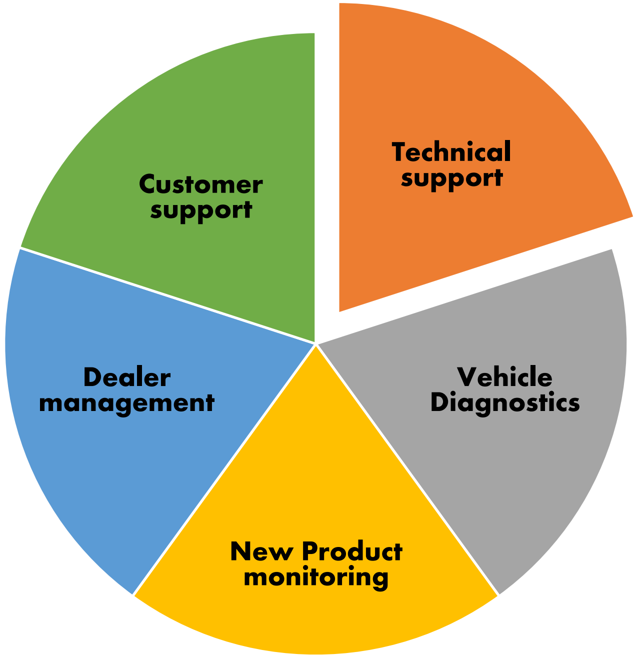
With Dr. Martin Corless, Professor, Dynamics and Controls, Aeronautics and Astronautics Engineering
Work: Consensus algorithms

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

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 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 responsibility and delivering consistently high KPI in region

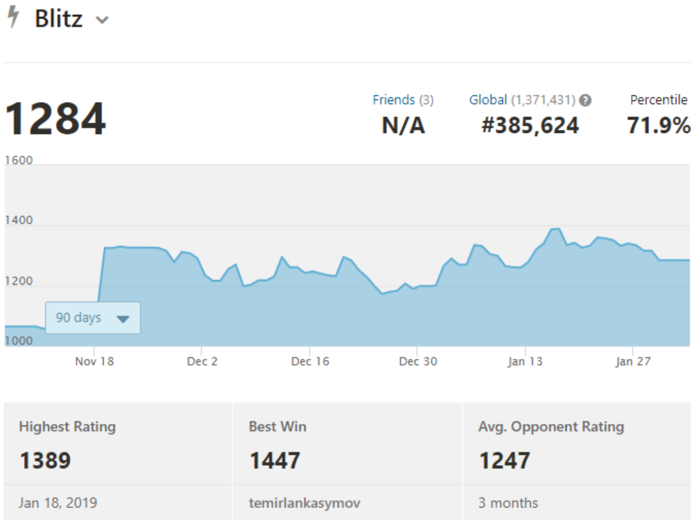


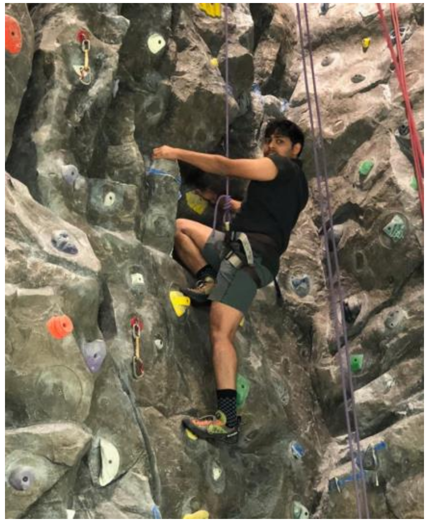
Aftersales Service Manager

Work at Volvo (2018)

- 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

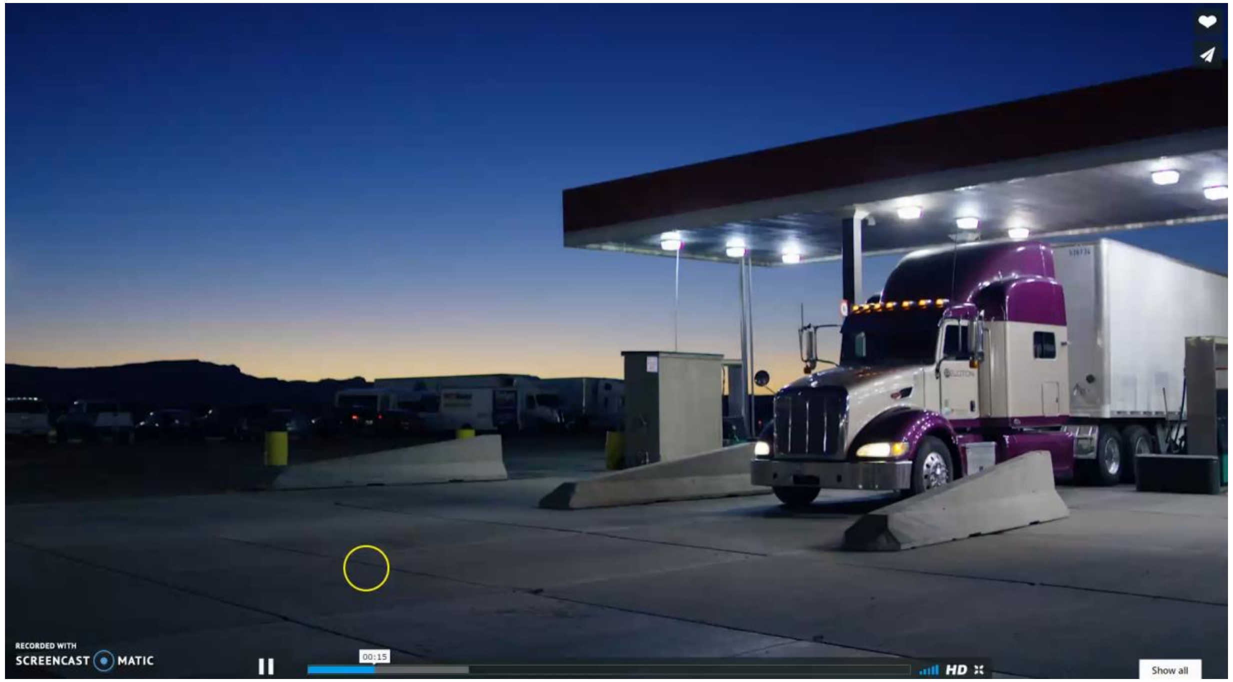
Hobbies





And more..

Decentralized controller for Multiagent systems – A motivation



Safety barrier Certificate: A review

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

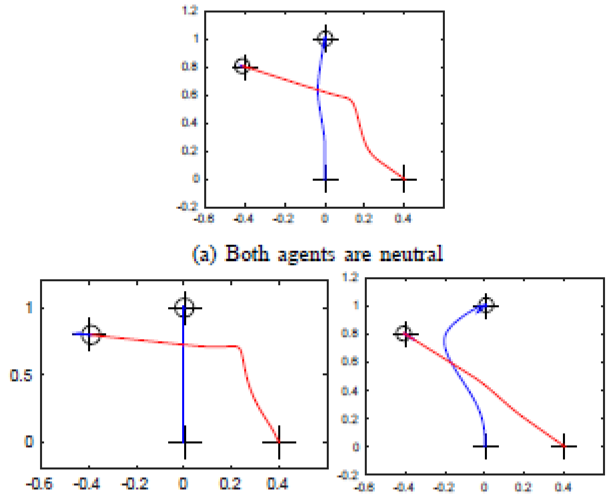
$$\begin{aligned} \mathcal{C} &= \{x \in \mathbb{R}^n : h(x) \geq 0\} \\ \partial\mathcal{C} &= \{x \in \mathbb{R}^n : h(x) = 0\} \\ \operatorname{Int}(\mathcal{C}) &= \{x \in \mathbb{R}^n : h(x) > 0\} \end{aligned}$$

$$\inf_{x \in \operatorname{Int}(\mathcal{C})} B(x) \geq 0, \qquad \lim_{x \to \partial\mathcal{C}} B(x) = \infty \qquad \dot{B} \leq \frac{\gamma}{B}$$

$$\frac{1}{\alpha_1(h(x))} \leq B(x) \leq \frac{1}{\alpha_2(h(x))}$$

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

Review (contd.)



(a) Both agents are neutral

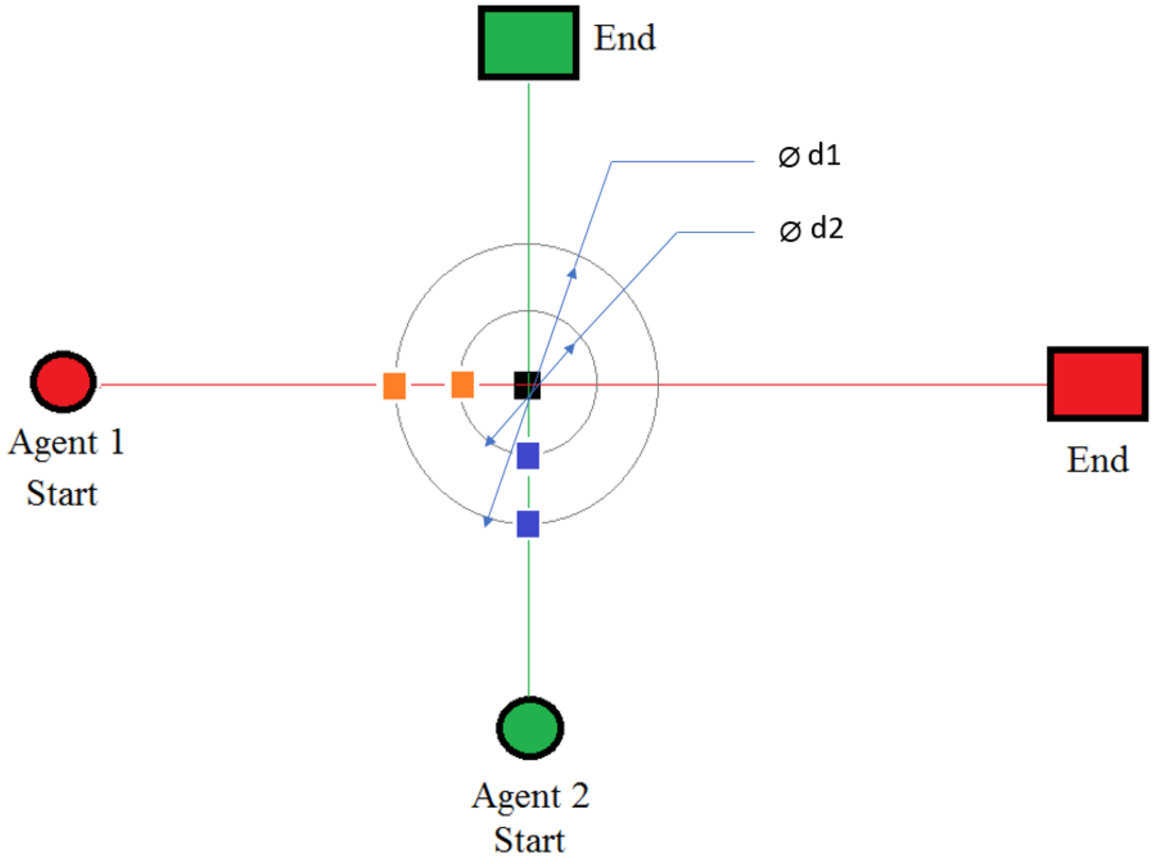
(b) Left agent aggressive

(c) Left agent conservative

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

$$\begin{aligned} \mathbf{u}^* = \underset{\mathbf{u}}{\operatorname{argmin}} \quad & J(\mathbf{u}) = \sum_{i=1}^{N} \|\mathbf{u}_i - \hat{\mathbf{u}}_i\|^2 \\ \text{s.t.} \quad & A_{ij}\mathbf{u} \leq b_{ij}, \qquad \forall i \neq j, \\ & \|\mathbf{u}_i\|_\infty \leq a_{max}, \ \ \forall i \in \mathcal{M} \end{aligned}$$

Problem representation



Problem formulation

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

where $p_i \in \mathbb{R}^2, v_i \in \mathbb{R}^2, u_i \in \mathbb{R}^2$ are the position, velocity and acceleration of the agent i

Table 1: Initial conditions and destination point

Agent	Initial position	Initial Velocity	Destination
Agent i	$\begin{bmatrix} p_{xi} \\ p_{yi} \end{bmatrix}$	$\begin{bmatrix} v_{xi} \\ v_{yi} \end{bmatrix}$	$\begin{bmatrix} r_{xi} \\ r_{yi} \end{bmatrix}$
Agent j	$\begin{bmatrix} p_{xj} \\ p_{yj} \end{bmatrix}$	$\begin{bmatrix} v_{xj} \\ v_{yj} \end{bmatrix}$	$\begin{bmatrix} r_{xj} \\ r_{yj} \end{bmatrix}$

Approach

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

$$A_i = A_j$$

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

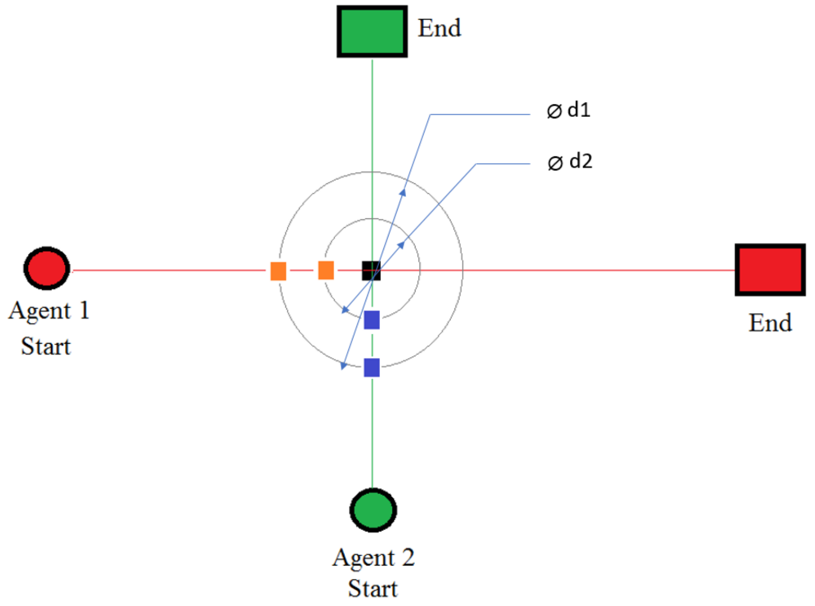
Target Point Control Design

$$d_{1i} = p_i - \frac{||\tau - p_i|| - d_1}{||\tau - p_i||}(\tau - p_i)$$

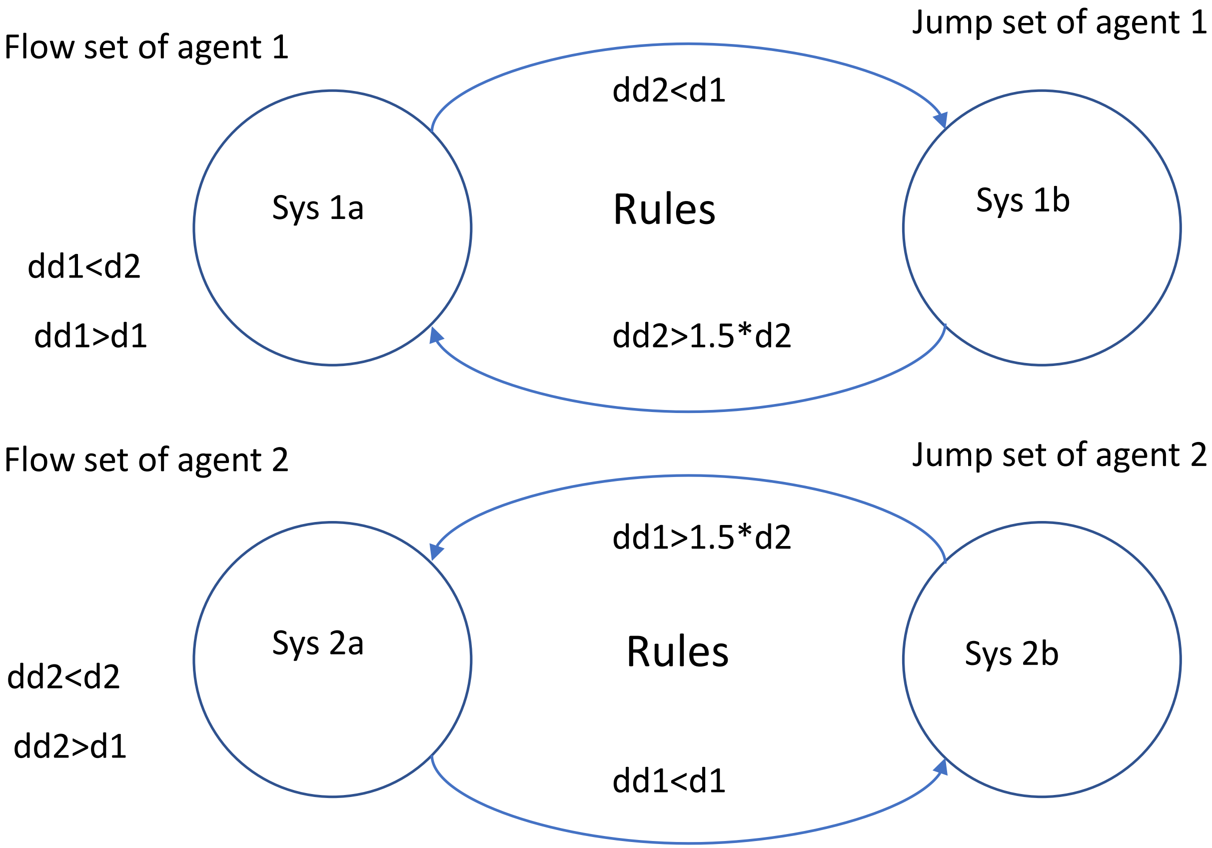
$$d_{2i} = p_i - \frac{||\tau - p_i|| - d_2}{||\tau - p_i||}(\tau - p_i)$$

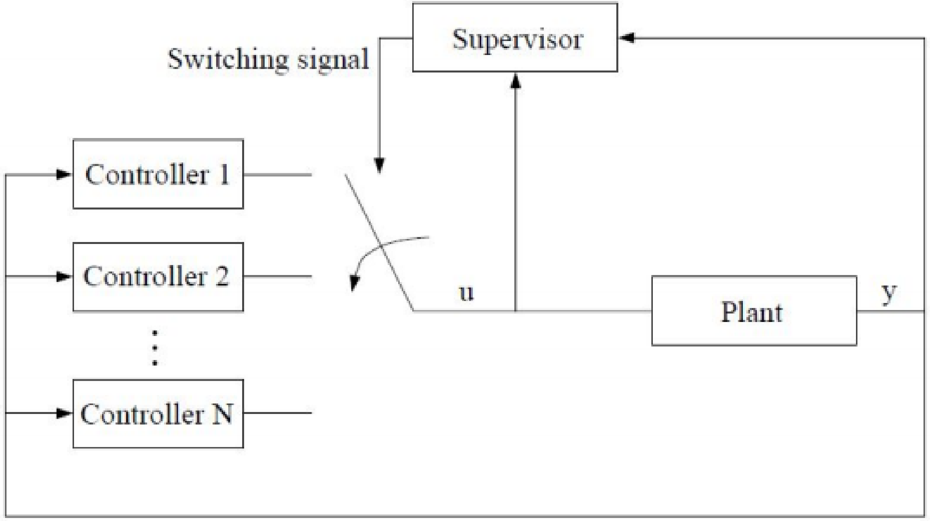
$$d_{1j} = p_j - \frac{||\tau - p_j|| - d_1}{||\tau - p_j||}(\tau - p_j)$$

$$d_{2j} = p_j - \frac{||\tau - p_j|| - d_2}{||\tau - p_j||}(\tau - p_j)$$



Hybrid distributed control

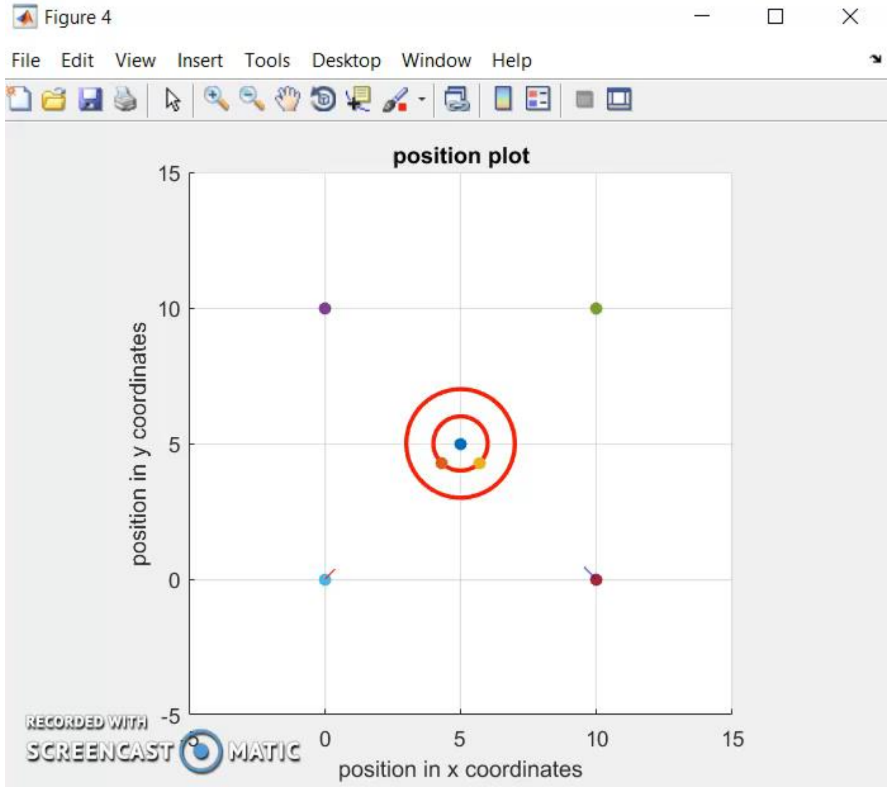




$$u_i = -k_1(p_i - r_i) - k_2 v_i$$

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

Simulation results



Genetic Algorithm based Path Selection for Unmanned Autonomous Vehicles (UAV)

Problem formulation

Figure 1: General schematic representation of problem

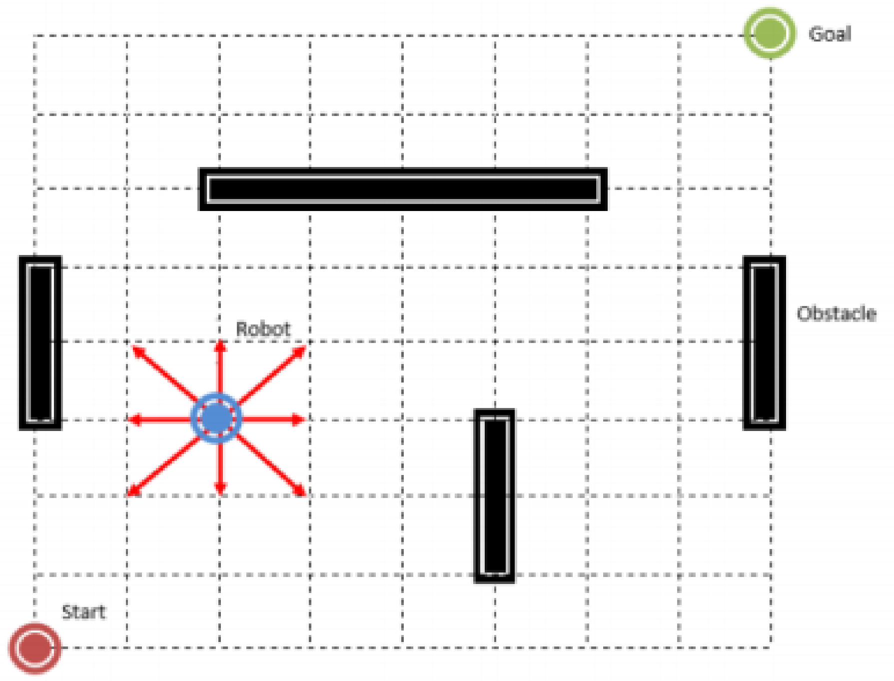
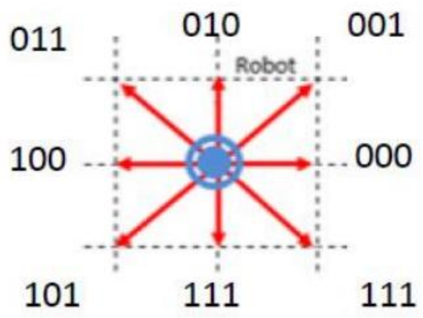


Figure 2: Decoding of design variable



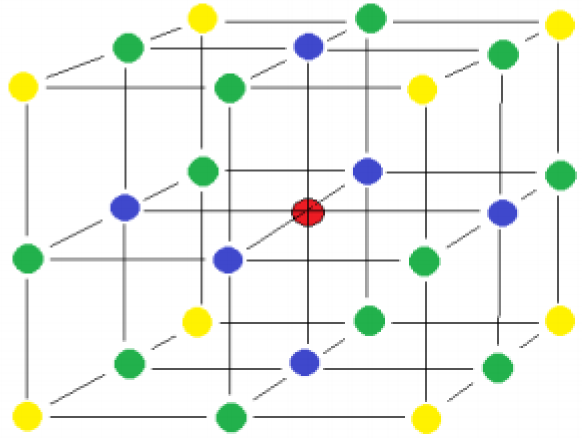


Figure 4: 3D representation showing possible movements. Points in Green, Yellow, Blue are at distances √2, √3,1 length units from robot respectively

Approach: Decoding design variables

x_i	Decoded	Distance	Direction
1	000	1	east
2	001	$\sqrt{2}$	northeast
3	010	1	north
4	011	$\sqrt{2}$	northwest
5	100	1	west
6	101	$\sqrt{2}$	southwest
7	110	1	south
8	111	$\sqrt{2}$	southeast

Evolution of GA – 2D case

Figure 3a: Generation 0

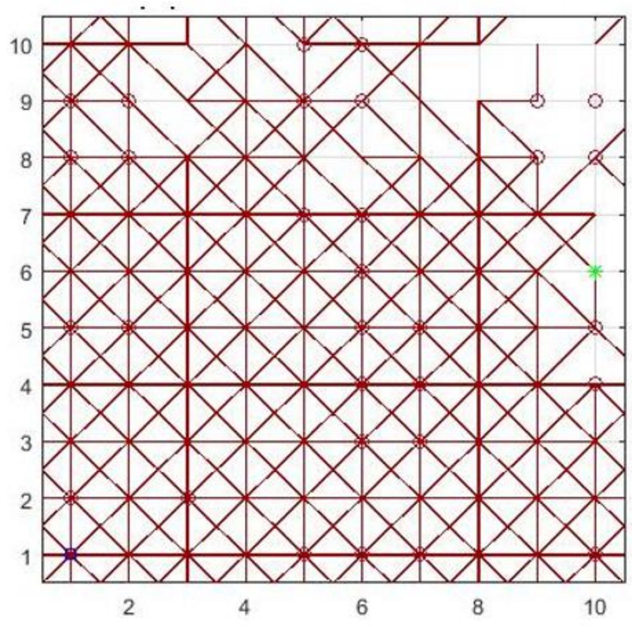
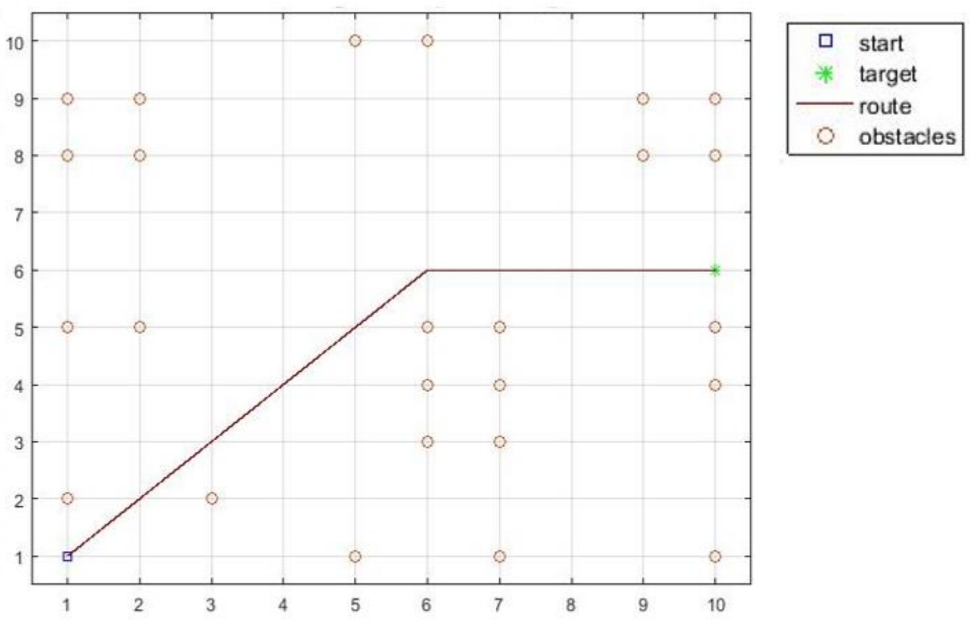
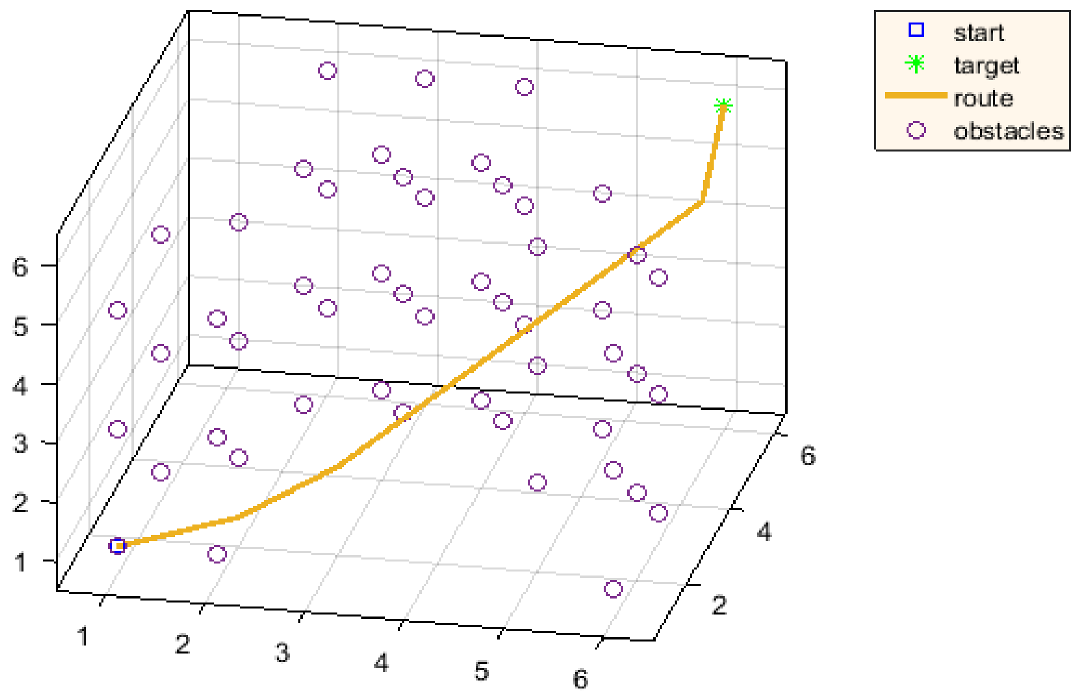


Figure 3b: Final Generation showing shortest path

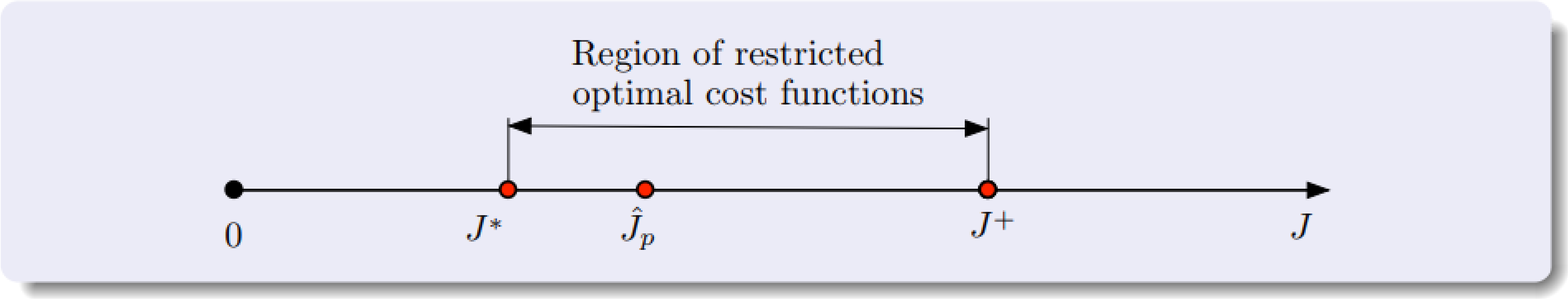


	Population size	Mutation probability	# generations	Fitness function	Shortest path distance	Convergence consecutive generations with best fitness value
Run 1	420	0.001202	127	10.17107	11.07107	25
Run 2	420	0.001202	162	10.17107	11.07107	25
Run 3	420	0.001202	135	10.17107	11.07107	25

GA results – 3D case



	Population size	Mutation probability	# generations	Fitness function	Shortest path distance	Convergence consecutive generations with best fitness value
Run 1	800	0.000628	73	8.166001	9.438793	25
Run 2	800	0.000628	125	8.166001	9.438793	25
Run 3	800	0.000628	121	8.166001	9.438793	25


Region of restricted
optimal cost functions
0
J^*
$\hat{J}_p$
J^+
J

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