

Granting Agencies: Department of Science and Technology,  
Indian Space Research Organization

# Time Optimal Feedback in Multi- Agent Systems

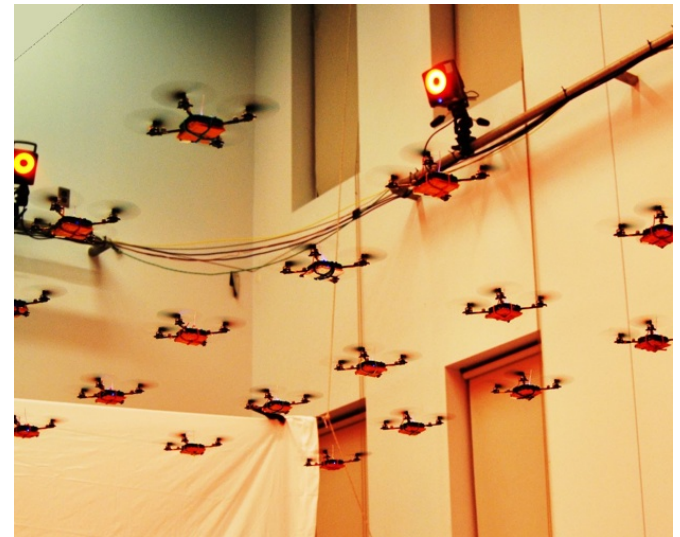
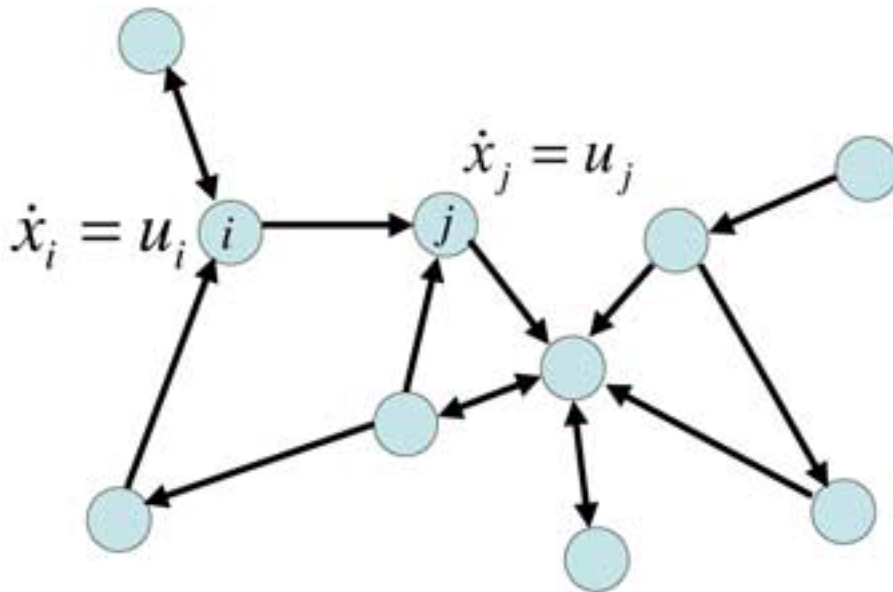
Joint Work with  
Deepak Patil, Ameer Mulla, and Sujay Bhatt

Debraj Chakraborty

Department of Electrical Engineering, Control and Computing Group

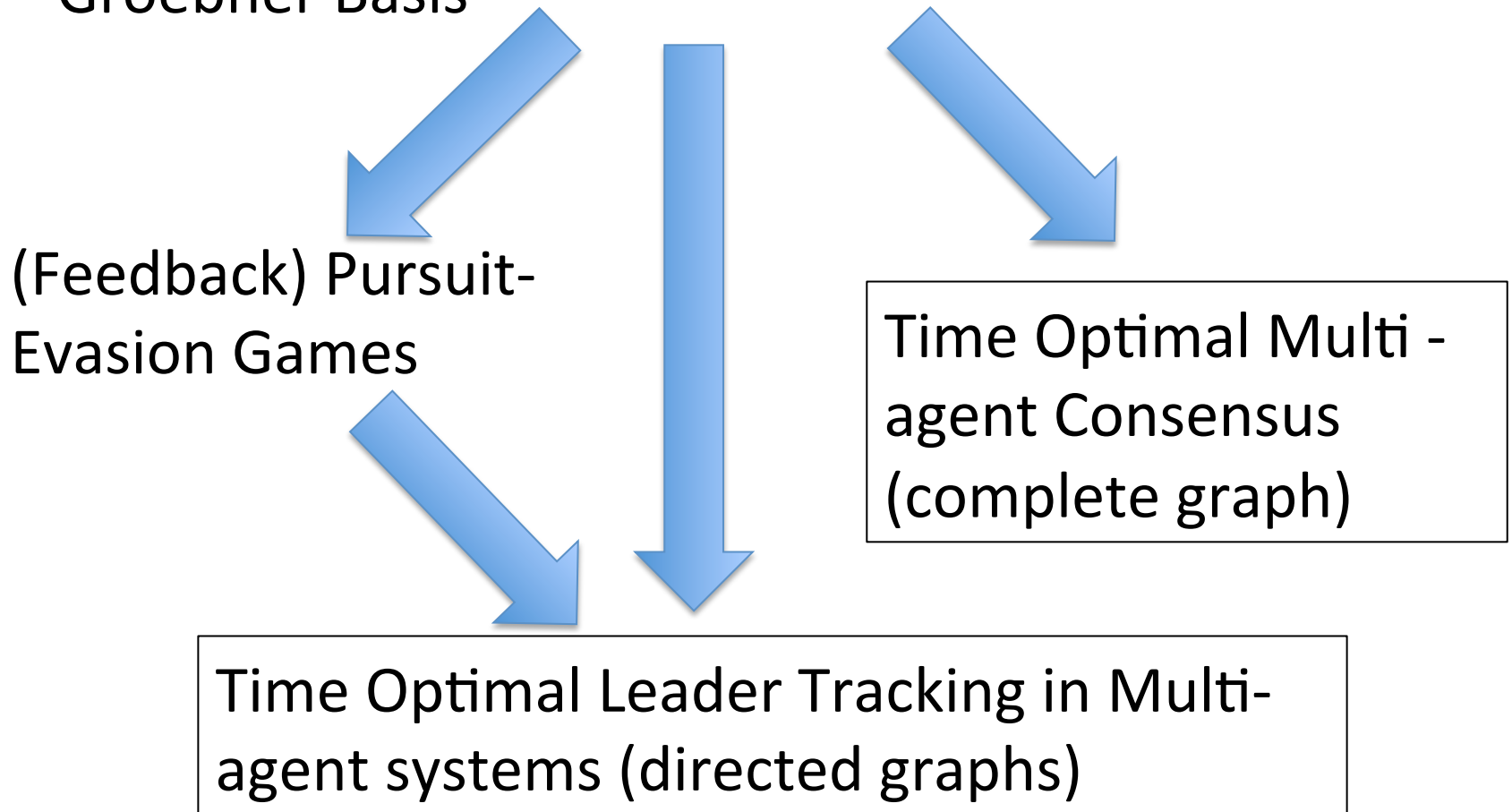
# Question

- Given a collection of autonomous dynamical systems (or 'agents') communicating with each other over (undirected/directed, time invariant/time varying) graph(s), how do we bring them to a consensus/synchronize them in minimum time?



# We solve two sub-questions

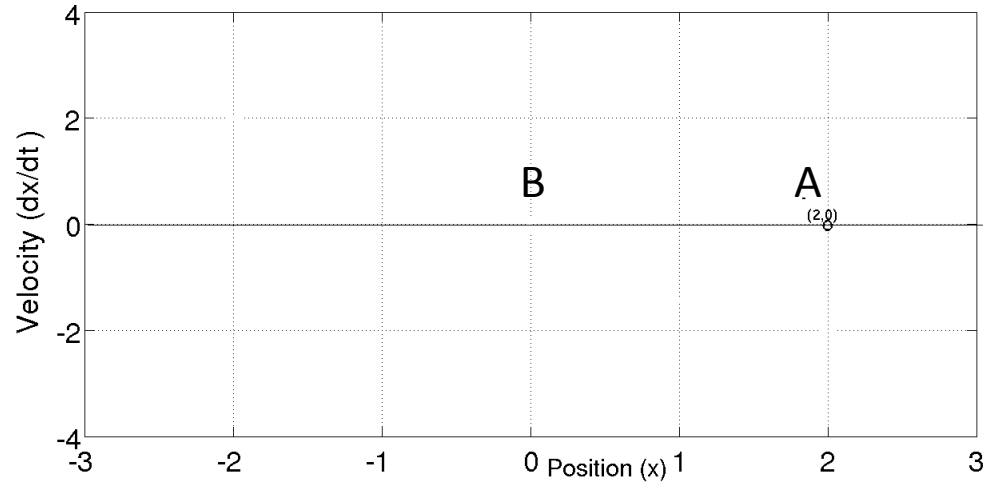
Computation of Time Optimal **Feedback** using Groebner Basis



# TIME OPTIMAL FEEDBACK



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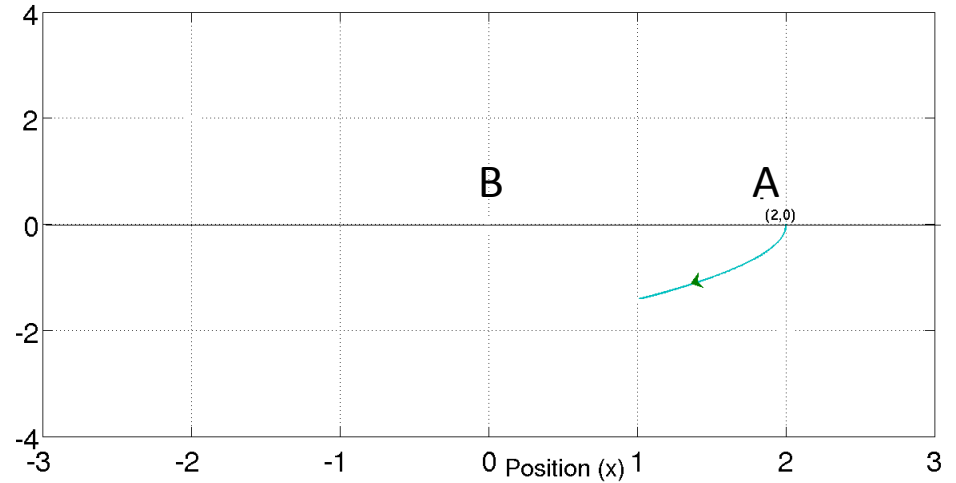
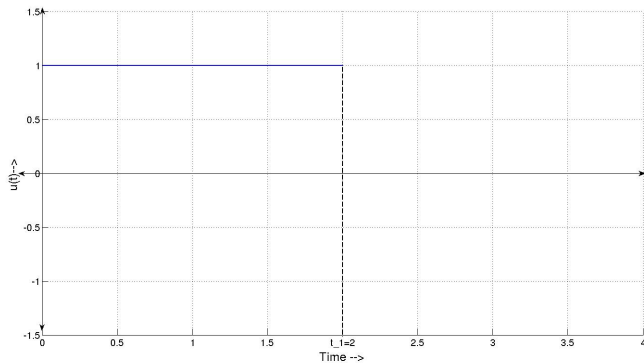
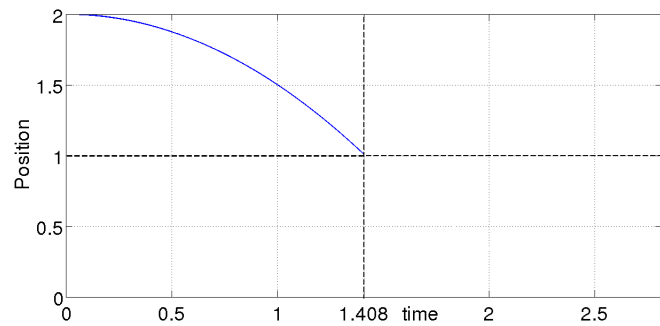
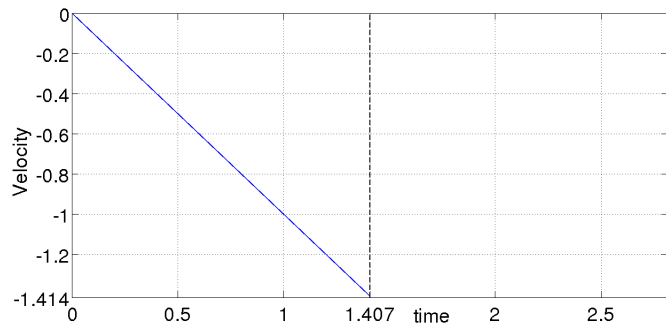


**Problem:** Go from A to B in minimum time with maximum allowed acceleration/deceleration =  $\pm 1$

$$\dot{p} = v; \quad \dot{v} = u$$

$$|u| \leq 1$$

# Time Optimal Feedback

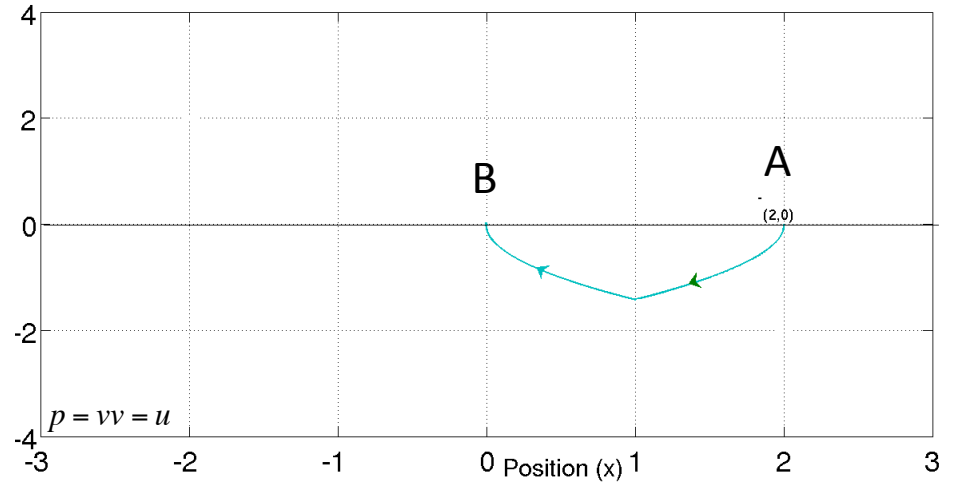
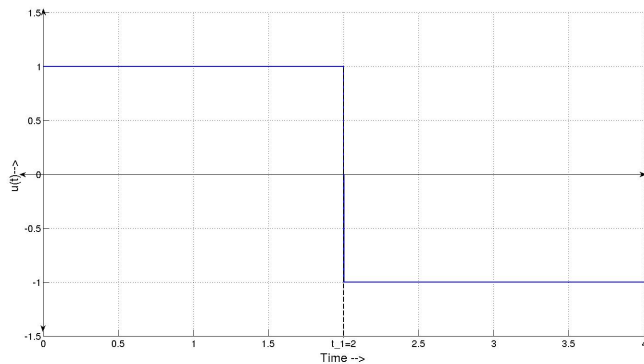
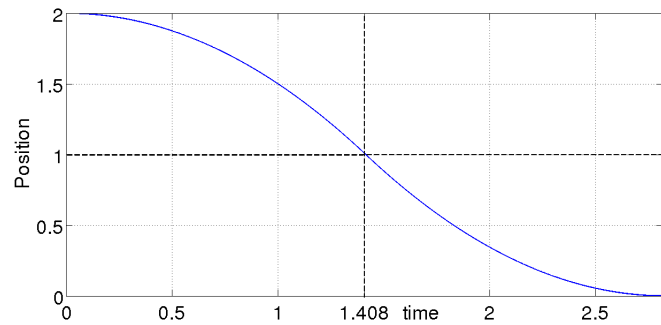
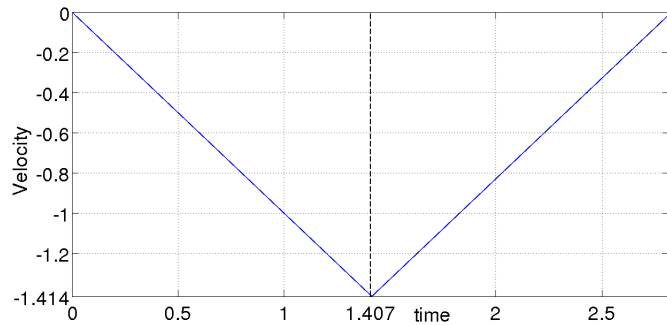


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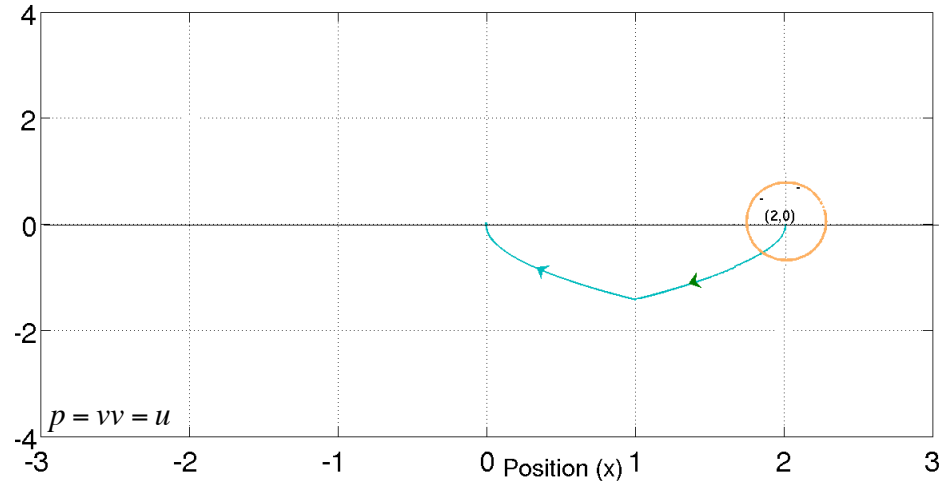
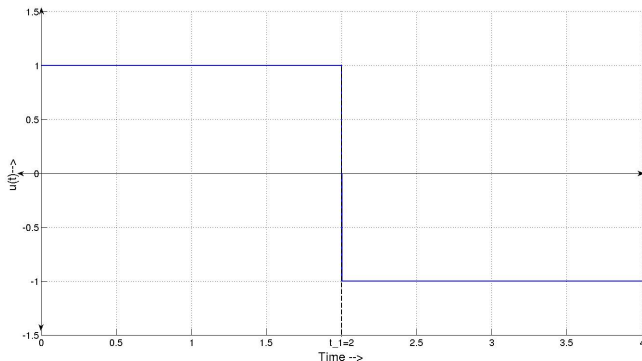
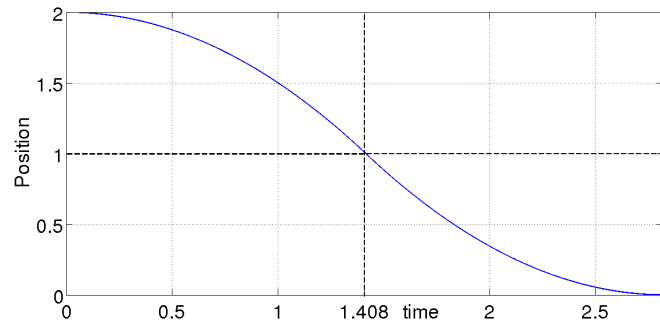
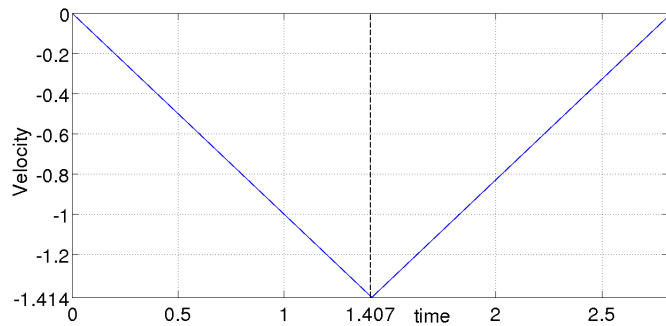


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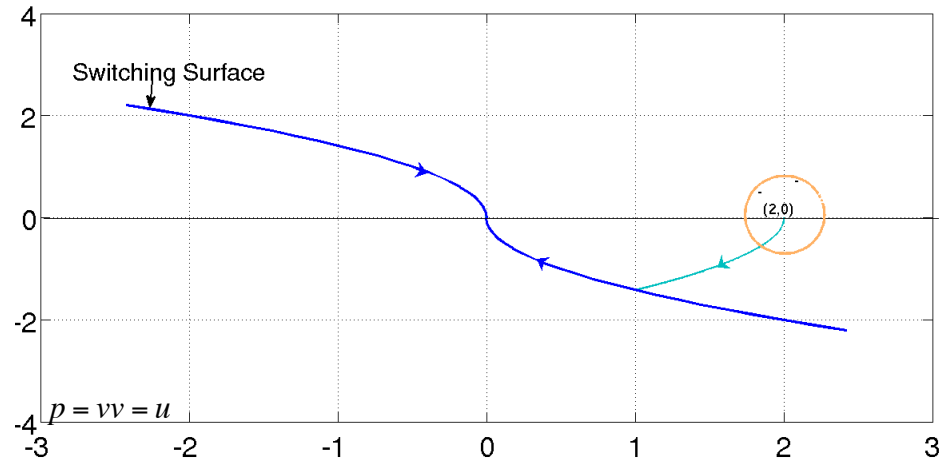
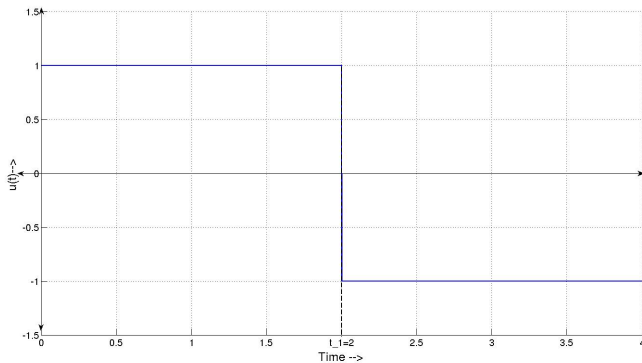
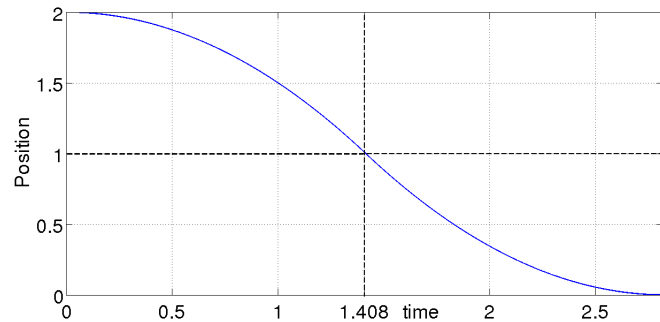
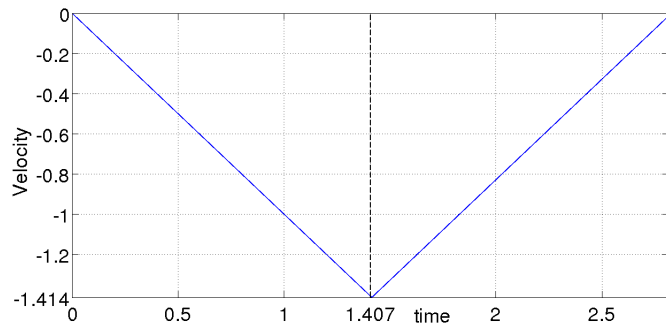
$$|u| \leq 1$$

**Q. What if A/B is perturbed?**

- Looks like we have to re-compute the switching instance all over again



# Time Optimal Feedback



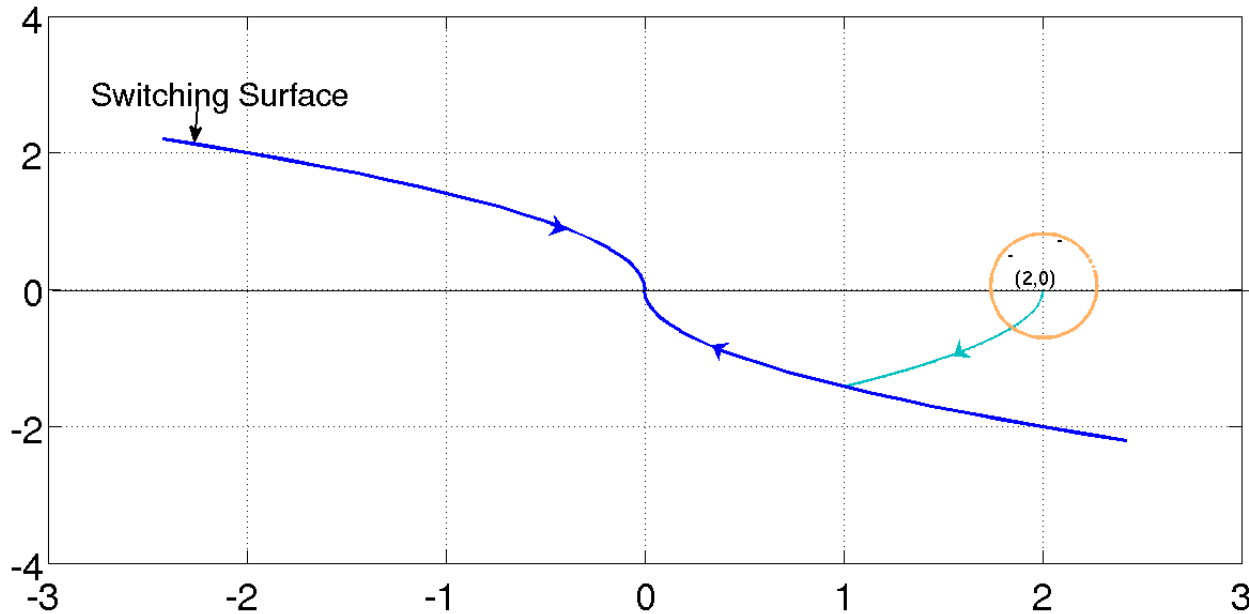
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- Looks like we have to re-compute the switching instance all over again

**NOT REALLY** – On state space, switching occurs based on the SWITCHING SURFACE – the blue line

# Switching Surface for Feedback

- If  $S$  (the switching surface) is known feedback control can be synthesized



**Feedback Algorithm:**

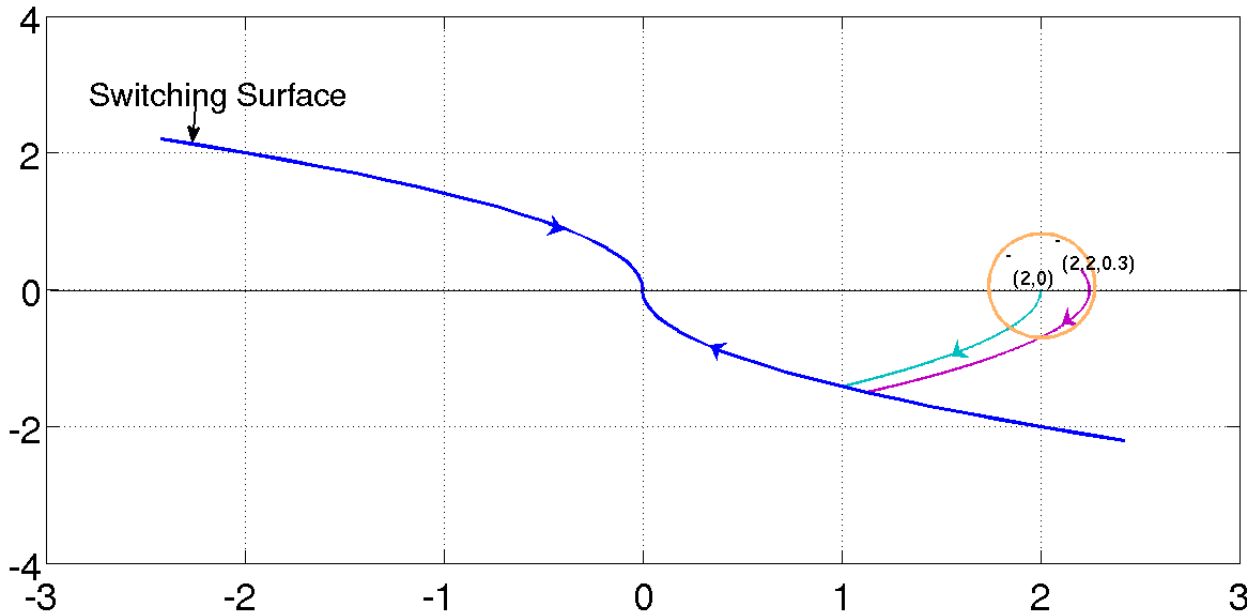
$$u = \begin{cases} +1 & \text{if } S < 0 \\ -1 & \text{if } S > 0 \end{cases}$$

And change sign as soon as

$$S = 0$$

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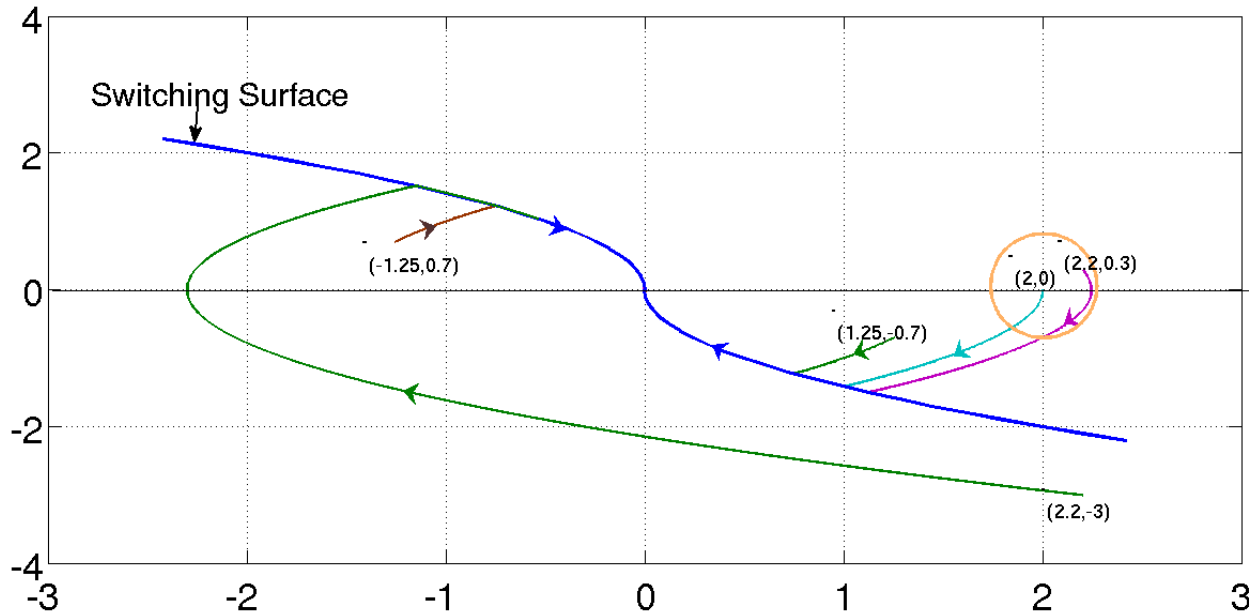
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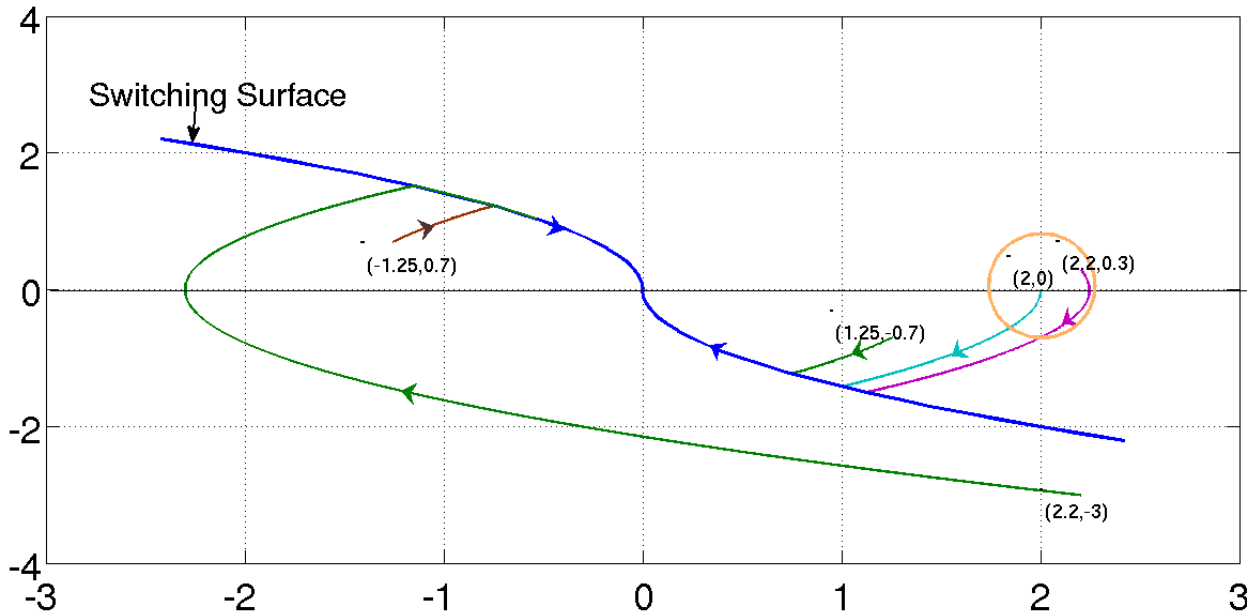
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- The virtues of feedback over open loop are many – In fact, the initial motivation for this research was ISRO RLV RCS thruster control design

# Switching Surface for Feedback

- But for this we need an **IMPLICIT** expression i.e.  $S(x_1, x_2) = 0$  equation for the switching surface



**Feedback Algorithm:**

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# Basic Idea

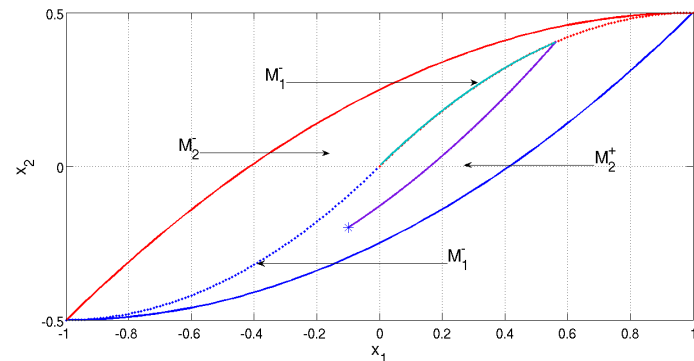
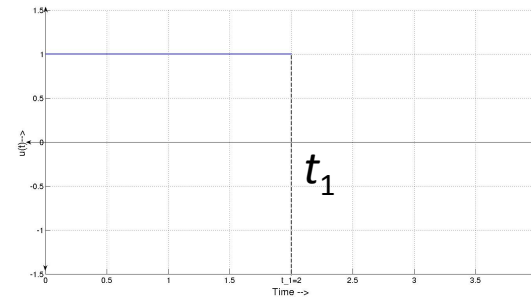
$$A = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}; \quad B = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad \begin{cases} \dot{x}_1 = x_1 + u \\ \dot{x}_2 = 2x_2 + u \end{cases}$$

Parametric Equations for the Switching Surface are easy – just solve above equations (for no switch, with origin target)

$$\left. \begin{aligned} 0 &= x_1 e^{t_1} \pm e^{t_1} \int_0^{t_1} e^{-\tau} d\tau \\ 0 &= x_2 e^{2t_1} \pm e^{2t_1} \int_0^{t_1} e^{-2\tau} d\tau \end{aligned} \right\}$$

$t_1$  is unknown and to be eliminated.

$$0 \leq t_1 < \infty$$



# Basic Idea

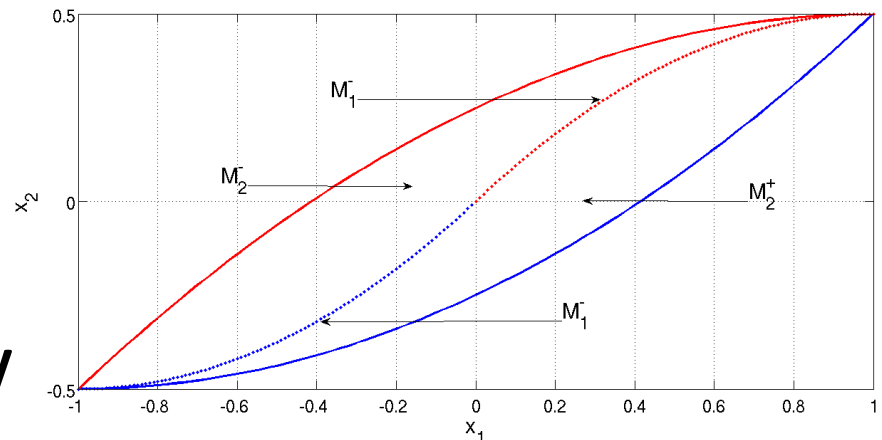
$$A = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}; B = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \left\{ \begin{array}{l} \dot{x}_1 = x_1 + u \\ \dot{x}_2 = 2x_2 + u \end{array} \right.$$

Solving: 
$$\left. \begin{array}{l} x_1 = \pm (e^{-t_1} - 1) \\ x_2 = \pm \frac{(e^{-2t_1} - 1)}{2} \end{array} \right\} \{x_1, x_2\} =: M_1$$

are the points from which we can go to the origin without further switching i.e.

Substitute:  $z_1 = e^{-t_1}$

Switching Surface: 
$$x_2 = \pm \frac{x_1^2}{2} + x_1$$



**Elimination not always this easy**

# How to eliminate?

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix}; B = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

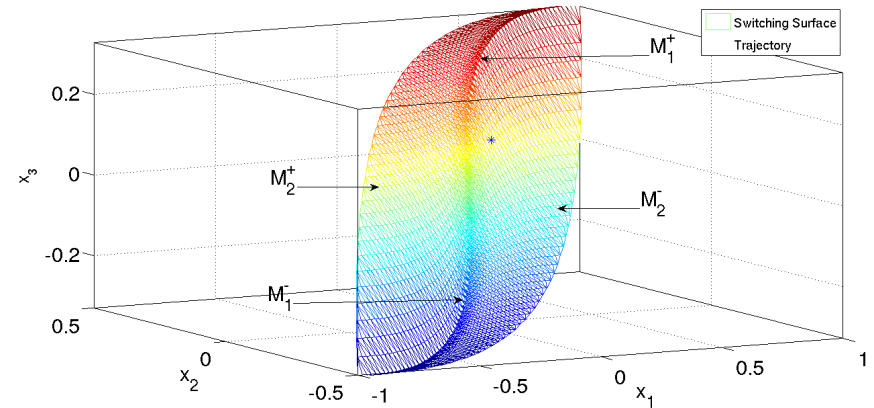
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$$0 \leq t_1 \leq t_2 < \infty$$

Things get complicated fast



- Set of points which can reach origin in ONE switch (colored surface above)
- Parametric representation of Switching Surface

**Q. How to eliminate  $t_1$  and  $t_2$ ?**



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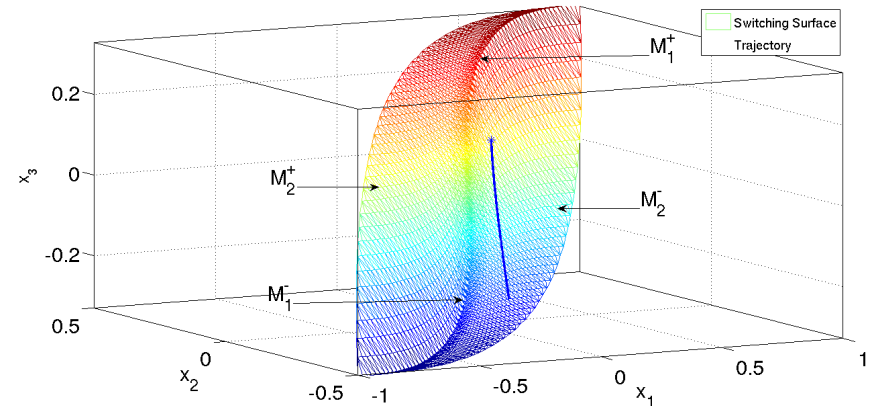
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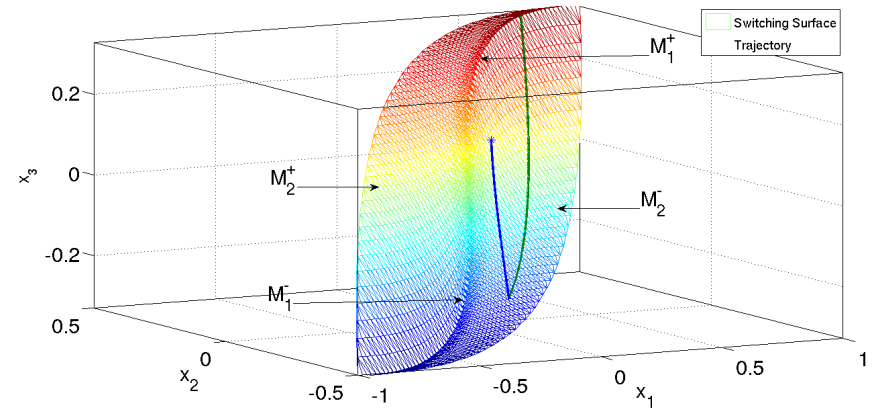
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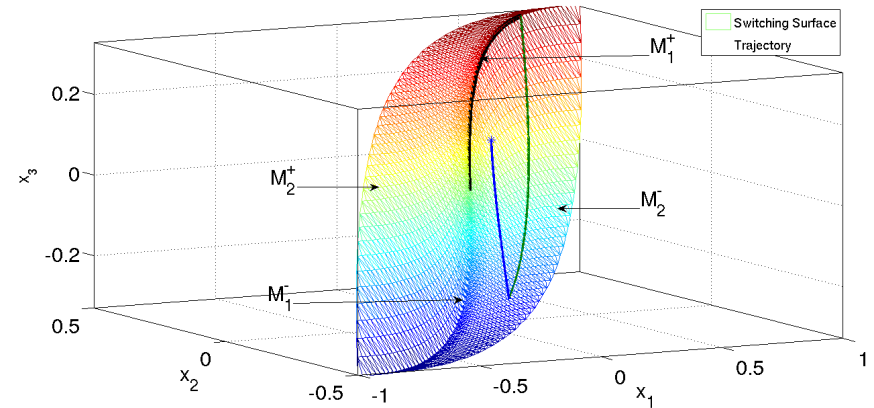
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# How to eliminate?

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix}; B = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

**Substitution to polynomials**

$$x_1 = 2e^{-t_1} - e^{-t_2} - 1$$

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$$0 \leq t_1 \leq t_2 < \infty$$

Set of points which can reach origin in ONE switch

$$\begin{array}{l} z_1 = e^{-t_1} \\ z_2 = e^{-t_2} \end{array}$$

$$x_1 = 2z_1 - z_2 - 1$$

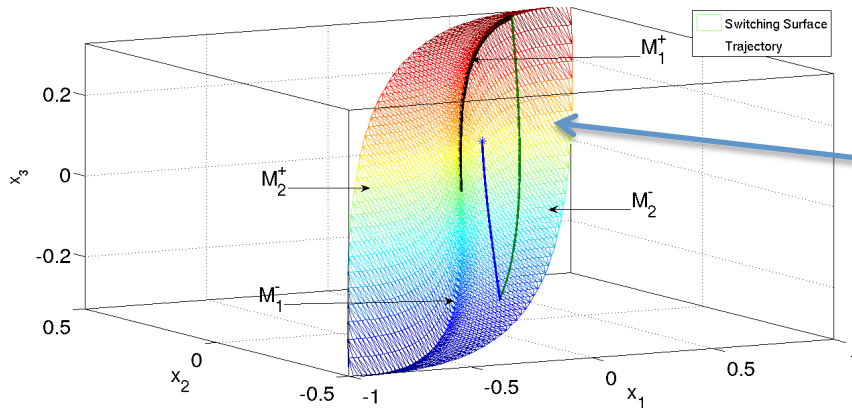
$$x_2 = z_1^2 - \frac{1}{2}z_2^2 - \frac{1}{2}$$

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$$0 < z_2 \leq z_1 \leq 1$$

Polynomial Parametric representation of Switching Surface

# How to eliminate?



$$g(x_1, x_2, x_3) = 0$$

+ the inequalities

Eliminate z's

$$x_1 = 2e^{-t_1} - e^{-t_2} - 1$$

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Set of points which can reach origin in ONE switch

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Polynomial Parametric representation of Switching Surface

# Elimination Algorithm

- Form an Ideal:

$$J = \left\langle x_1 - 2z_1 + z_2 + 1, x_2 - z_1^2 + \frac{1}{2}z_2^2 + \frac{1}{2}, x_3 - \frac{2}{3}z_1^3 + \frac{1}{3}z_2^3 + \frac{1}{3} \right\rangle$$

- Compute Groebner basis  $G$  of  $J$  with lexicographic ordering  $z_1 \succ z_2 \succ x_1 \succ x_2 \succ x_3$ .
- The element  $g \in G \cap Q[x_1, x_2, x_3]$  defines the smallest variety containing the parametric representation of the switching surface
- Inequality constraints:  $z_1$  and  $z_2$  can be computed in terms of the states (skipped here)

# Example

## Example

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix} \text{ and } B = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}.$$

- Form an ideal  $J = \langle x_1 - 2z_1 + z_2 + 1, x_2 - z_1^2 + \frac{1}{2}z_2^2 + \frac{1}{2}, x_3 - \frac{2}{3}z_1^3 + \frac{1}{3}z_2^3 + \frac{1}{3} \rangle$ .
- Using Elimination Algorithm compute  $g_2^+(x_1, x_2, x_3) = 0$ .
- Also compute  $z_1 = \frac{-(-x_1^3 - 3x_1^2 - 3x_1 + 3x_3)}{(3x_1^2 + 6x_1 - 6x_2)}$  and  $z_2 = \frac{-(x_1^3 + 3x_1^2 - 6x_1x_2 - 6x_2 + 6x_3)}{(3x_1^2 + 6x_1 - 6x_2)}$
- Thus  $M_2^+ = \{(x_1, x_2, x_3) : g_2^+(x_1, x_2, x_3) = 0, 0 < z_2 \leq z_1 \leq 1\}$

# Guarantees

- $g(x_1, x_2, x_3)$  can be 'cut-out' to recover the actual switching surface.
- Switching based on  $g(x_1, x_2, x_3)$  works.
- Inaccurate/practical switching converges to arbitrary neighborhood of origin
- The null controllable set can be algebraically computed.
- Limit cycles occur for most non-origin targets - time period can be computed

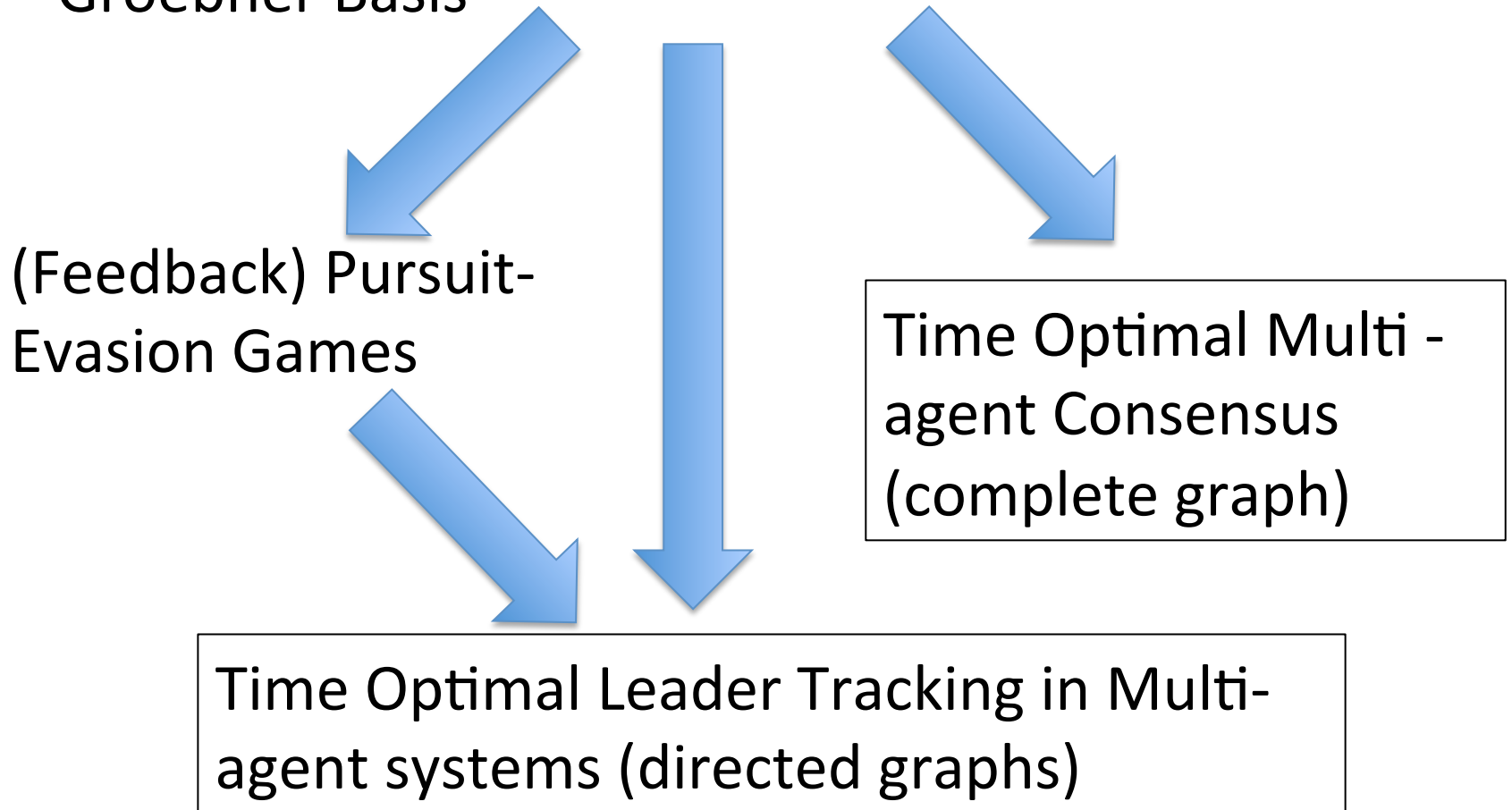
**The Good: Time Optimal + works for entire null controllable region + feedback control**

**The Bad – only works for rational/imag eigenvalues-  
*recently some hope of removing this limitation***



# Plan

Computation of Time Optimal **Feedback** using Groebner Basis



# Pursuit Evasion Games



# Time Optimal (Feedback) Pursuit Evasion

- Optimal Feedback strategy was hard to compute: can be computed now (for rational/imaginary eigenvalues)

$$\dot{x}_e = Ax_e + Bu_e; \quad |u_e| \leq \alpha$$

$$\dot{x}_p = Ax_p + Bu_p \quad |u_p| \leq \beta$$

Problem: 'e' tries to maximize and 'p' tries to minimize the time T when

$$x_e(T) = x_p(T)$$

# Pursuit Evasion Games - Assumptions

- P and E do not know each others strategies
- Each needs to guard against worst possible strategies of the other
- Proposed pursuer control strategy (similarly for evader):

$$u_p^*(t) = \arg \min_{|u_p| \leq \beta} \left( \max_{|u_e| \leq \alpha} T(u_p, u_e) \right)$$

$T(u_p, u_e)$  is capture time

$u_p^*(t)$ : min-max control strategy for pursuer

# Trick: Difference System

- Difference System:

$$\dot{x}(t) = Ax(t) + Bu_{ep}(t)$$

where,  $x(t) = x_p(t) - x_e(t)$  and  $u_{ep}(t) = u_p(t) - u_e(t)$

- Capture condition:  $x_p(t) = x_e(t) \implies x(t) = 0$  for some  $t \geq T$
- Objective function:

$$J = \int_0^T 1 dt = T(u_p, u_e)$$

- Min-max strategies:  $u_p^*$  and  $u_e^*$  such that

$$J^* = T(u_p^*, u_e^*) = \min_{|u_p| \leq \beta} \max_{|u_e| \leq \alpha} T(u_p, u_e)$$

# Bryson and Ho (1969)

- Hamiltonian:  $H = \lambda^T (Ax + B(u_p - u_e)) + 1$
- Necessary condition for stationarity of  $J$

$$\dot{\lambda} = -\frac{\partial H}{\partial t} = -A^T \lambda \quad \lambda(0) = \lambda_0$$

$$H^* = \min_{|u_p| \leq \beta} \max_{|u_e| \leq \alpha} (\lambda^T (Ax + B(u_p - u_e)) + 1)$$

- Optimal inputs:

$$u_e^*(t) = \arg \max_{u_e} H(u_p, u_e) = -\alpha \text{sign}(\lambda_0^T e^{-At} B)$$

$$u_p^*(t) = \arg \min_{u_p} H(u_p, u_e^*) = -\beta \text{sign}(\lambda_0^T e^{-At} B)$$

- $u_p^*$  and  $u_e^*$  should have same sign and switch according to same switching function.

# Switching Surface

$$u_e^*(t) = \arg \max_{u_e} H(u_p, u_e) = -\alpha \text{sign}(\lambda_0^T e^{-At} B)$$

$$u_p^*(t) = \arg \min_{u_p} H(u_p, u_e^*) = -\beta \text{sign}(\lambda_0^T e^{-At} B)$$

A switching surface corresponding to this switching function can be computed by considering the difference system

- The “difference” system:

$$D: \dot{x}_p - \dot{x}_e = A(x_p - x_e) + B(u_p - u_e); \quad |u_p - u_e| \leq \beta - \alpha$$

- Capture when  $D$  reaches origin = Time Optimal transfer to origin with the changed input bound
- Feedback pursuit-evasion strategies can be computed
- Capture can be guaranteed if  $\alpha < \beta$

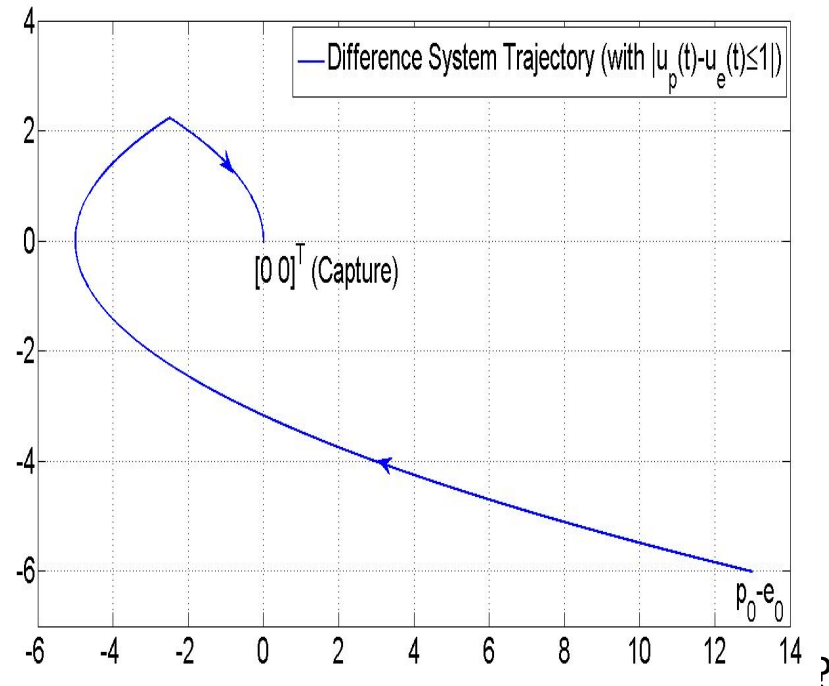
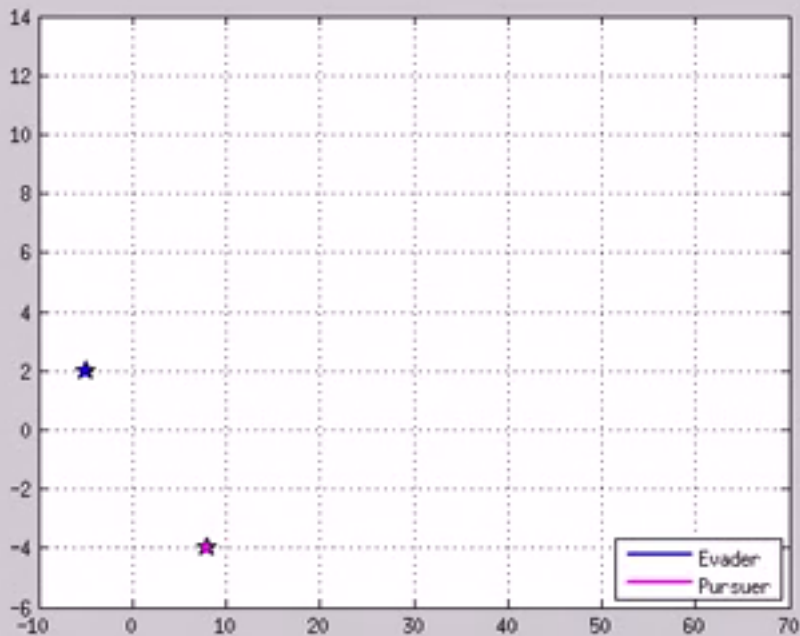
# Example Pursuit Evasion

$$\dot{p}_p = v_p; \dot{v}_p = u_p$$

$$|u_p| \leq 2$$

$$\dot{p}_e = v_e; \dot{v}_e = u_e$$

$$|u_e| \leq 1$$



'p' plays **min-max feedback** while e plays **max-min feedback** strategy, but still gets captured.



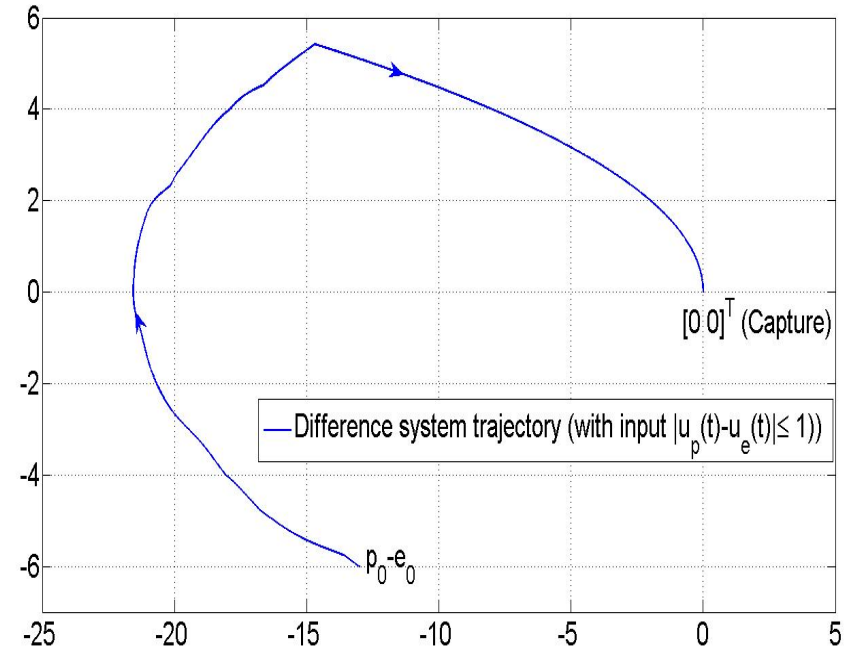
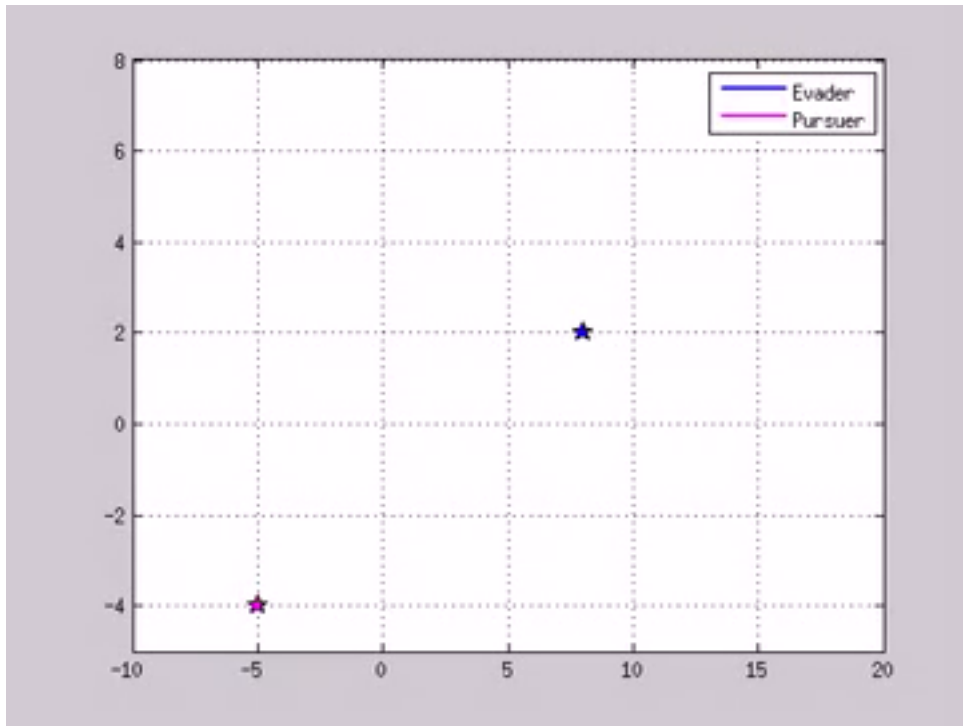
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$$\dot{p}_p = v_p; \dot{v}_p = u_p$$

$$|u_p| \leq 2$$

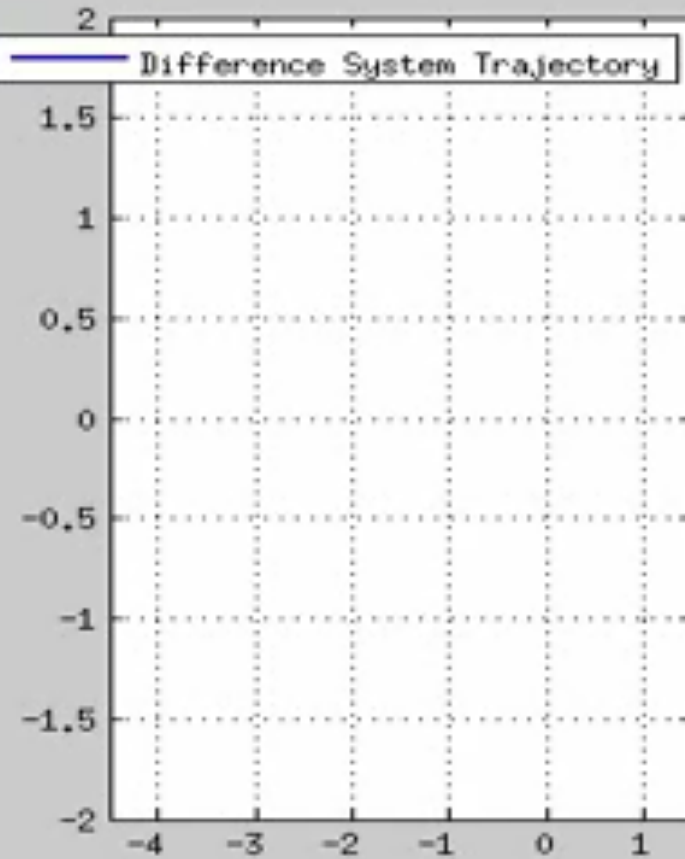
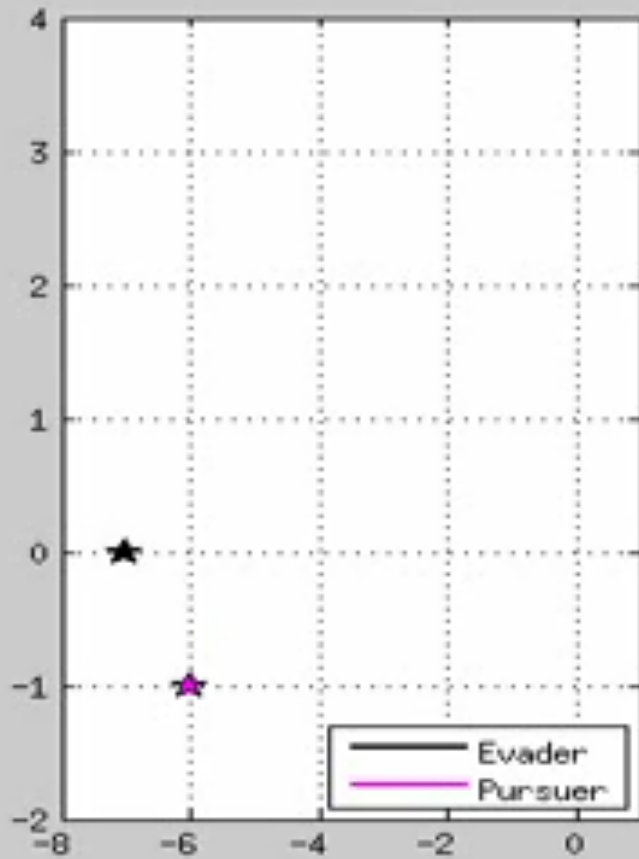
$$\dot{p}_e = v_e; \dot{v}_e = u_e$$

$$|u_e| \leq 1$$



'p' plays **min-max feedback** while e plays **NON-OPTIMAL** strategy, gets captured earlier.

# Successful Escape



# Time Optimal Leader Tracking in Multi-agent systems

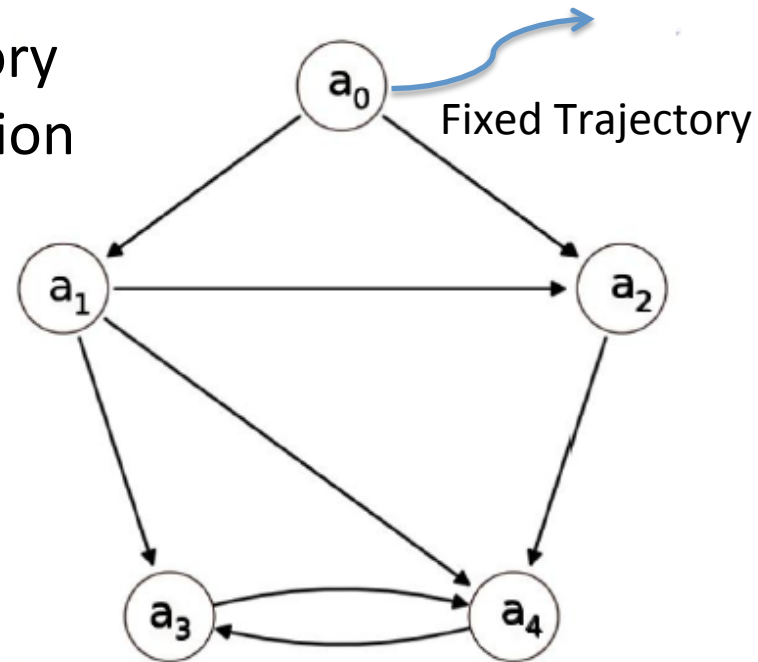


# Consensus Tracking for Multiple Agents

## Assumptions:

- All agents are stable with identical dynamics and input bounds
- $a_0$  is the leader
- $a_0$  moves along a given fixed trajectory
- State information flows in the direction of the arrows (directed graph)

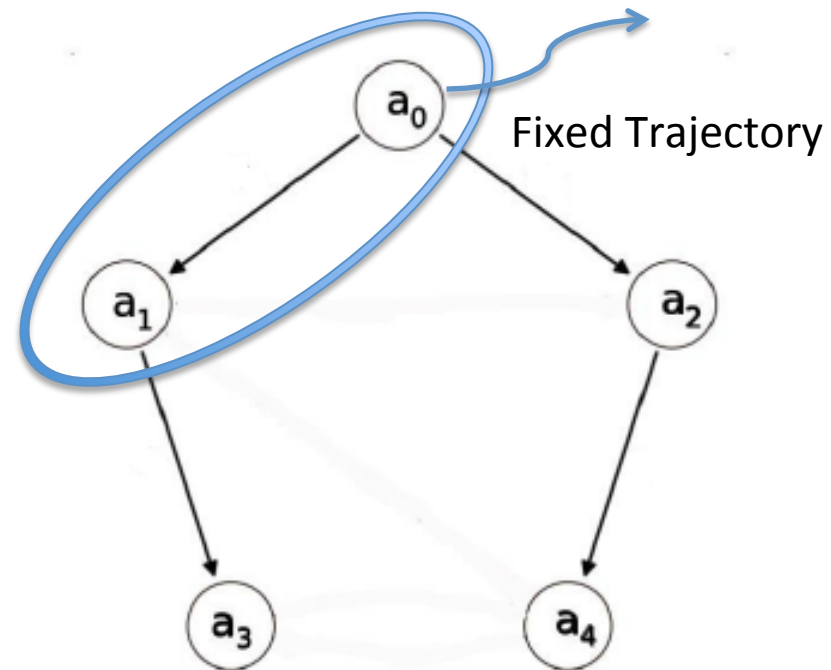
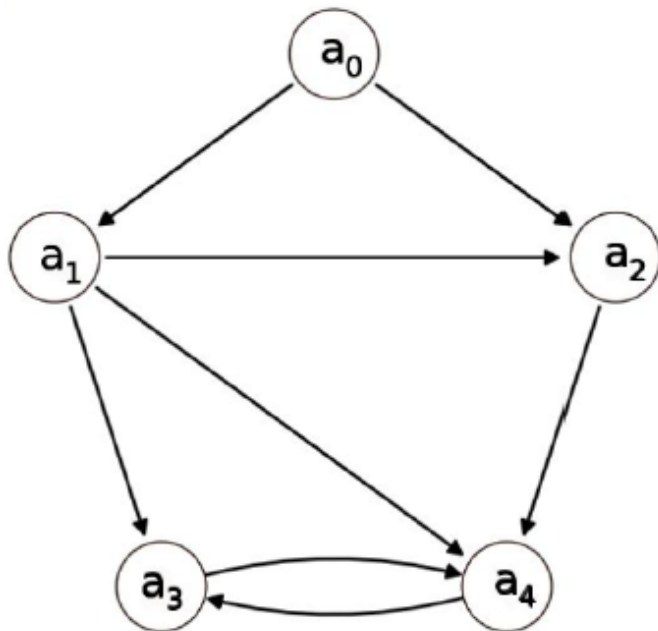
**Problem:** Find the *local* control laws for  $a_1, \dots, a_4$  such that all of them track  $a_0$ 's trajectory in the minimum time possible.



**Assumption:**  $a_0$  is “capturable” by the followers

# Min-Max Pursuit

- Identify a directed spanning tree rooted at the leader (later)
- Apply the min-max pursuit policy for each follower
- For example: consider  $(a_0, a_1)$  pair and apply the min-max pursuit policy for  $a_1$

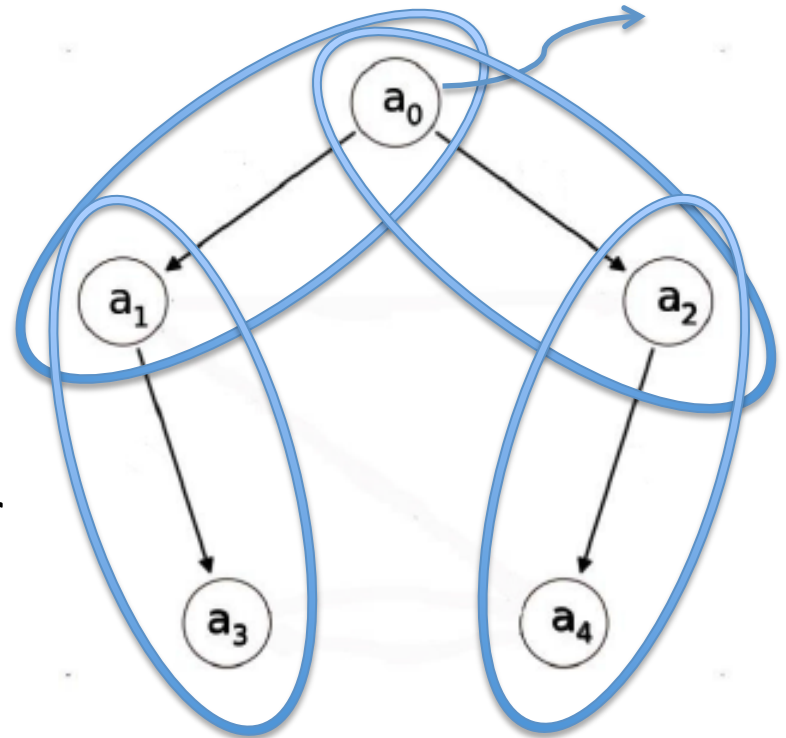


# Min-Max Pursuit

- Identify a directed spanning tree rooted at the leader (later)
- Apply the min-max pursuit policy for each follower
- For example: consider  $(a_0, a_1)$  pair and apply the min-max pursuit policy for  $a_1$
- Similarly for all pairwise leader-follower pairs
- For each pair the upper bound on capture time is given by:

$$\bar{t}_{ij} = \min_{|u_i| \leq \beta_i} \max_{|u_j| \leq \beta_j} T(u_i, u_j)$$

- But there is no upper bound for identical bounds on the leader and follower



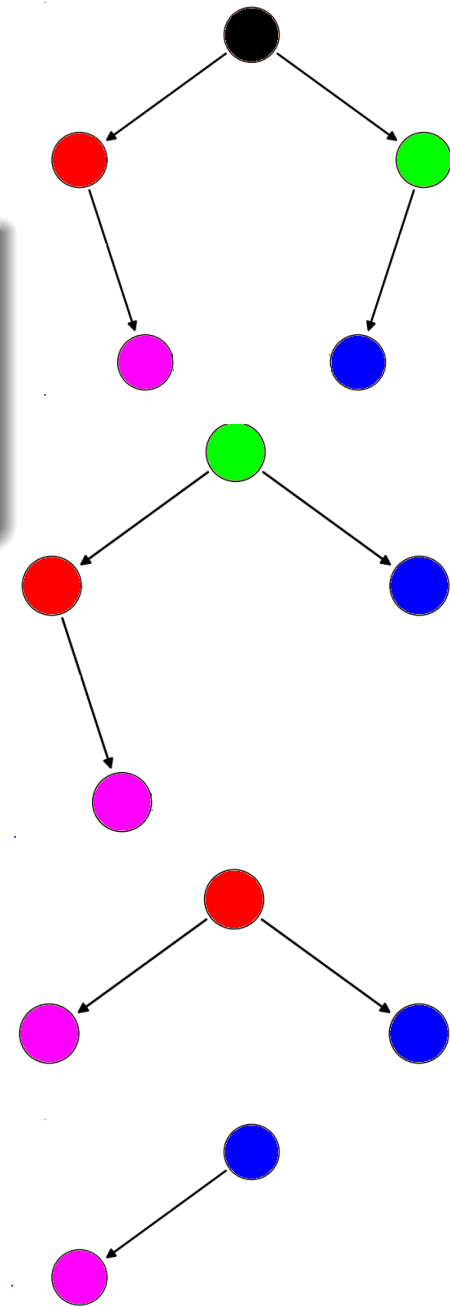
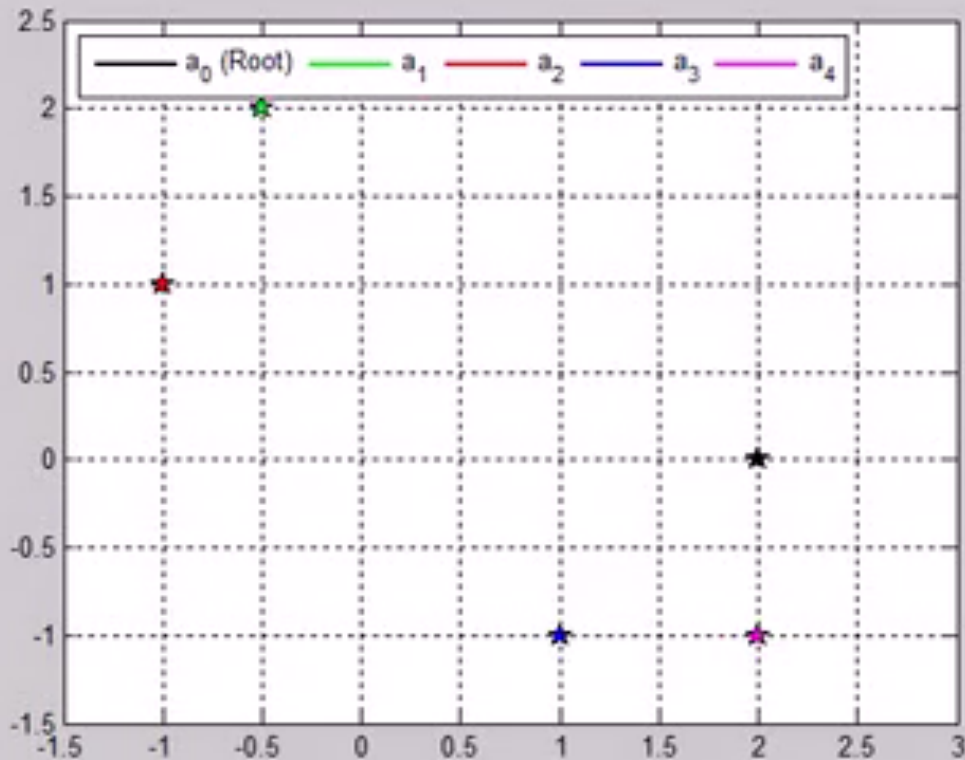
# Min Time Leader Tracking

## Example

5-agent systems communicating over a tree. Agent dynamics is given by

$$\dot{x}_i(t) = \begin{bmatrix} -1 & 0 \\ 0 & -2 \end{bmatrix} x_i(t) + \begin{bmatrix} 1 \\ 1 \end{bmatrix} u_i(t) \quad \text{for } i = 0, 1, \dots, 4$$

$|u_0(t)| \leq 1$  and  $|u_i(t)| \leq 3$  for  $i = 1, \dots, 4$



# Selection of Directed Spanning Tree

- We have an algorithm which does this with local information (skipped here)
- How does the selection of the spanning tree affect time to consensus?
- Does using information from multiple leaders help reduce time to consensus?
- How do cycles (if allowed to remain) affect time to consensus?



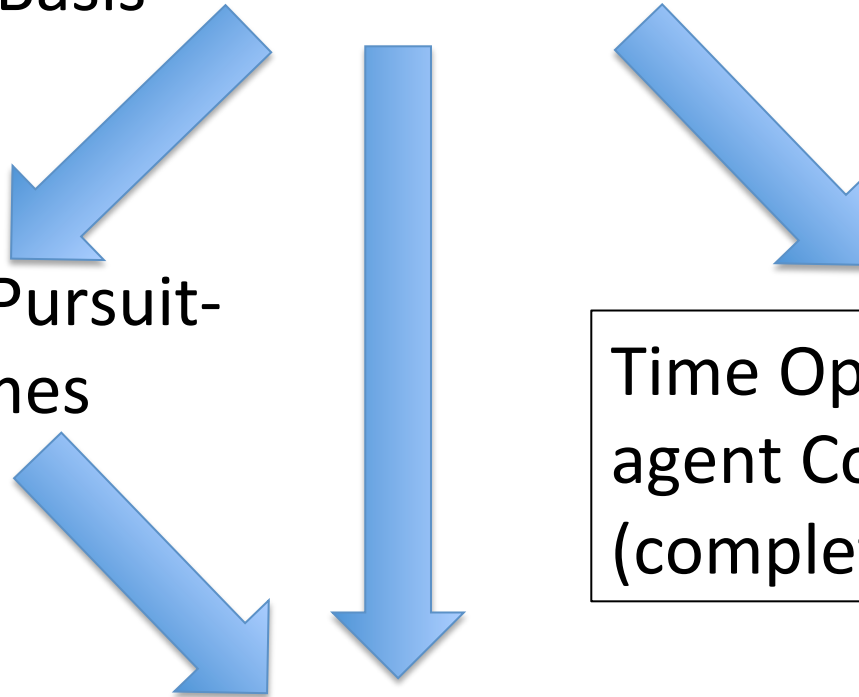
# Plan

Computation of Time Optimal **Feedback** using Groebner Basis

(Feedback) Pursuit-Evasion Games

Time Optimal Multi-agent Consensus (complete graph)

Time Optimal Leader Tracking in Multi-agent systems (directed graphs)



# Multi Agent: Minimum Time Consensus

**Consensus:** Many 'agents' try to reach a previously unspecified point autonomously



# Min Time Consensus

- **Problem:** Consider  $N$  double integrator 'agents' communicating over a complete graph

$$\dot{x}_i(t) = \underbrace{\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}}_A x_i(t) + \underbrace{\begin{bmatrix} 0 \\ 1 \end{bmatrix}}_b u_i(t) \quad i = 1, \dots, N$$

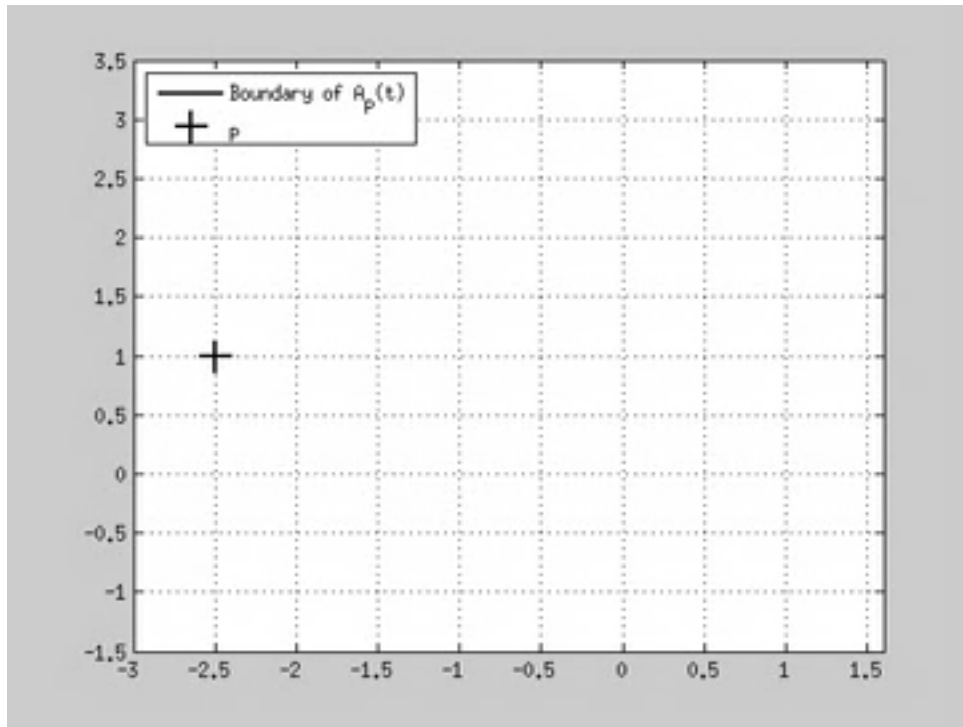
with  $x_i(t) = \begin{bmatrix} r_i(t) \\ v_i(t) \end{bmatrix}$ ,  $x_i(0) = x_{i0} = \begin{bmatrix} r_{i0} \\ v_{i0} \end{bmatrix}$  and  $|u_i(t)| \leq 1$ .

Find  $\bar{x}$  and  $\min \bar{t}$  such that, for all  $i, j$   
 $x_i(\bar{t}) = \bar{x}$  and  $x_i(t) = x_j(t)$  for all  $t \geq \bar{t}$

# Attainable Set

## Attainable Set from p at time t

$$\mathcal{A}_p(t) = \left\{ x : x = e^{At} p + \int_0^t e^{A(t-\tau)} b u(\tau) d\tau, \forall u(t) : |u(t)| \leq 1 \right\}$$



- Each point on the boundary can be reached using bang-bang time optimal control.
- **Polynomial Expressions for the boundaries can be obtained**

# Main Idea

- For consensus, it would seem that the attainable sets of all the agents need to intersect, i.e. for consensus at time  $t$

$$\bigcap_{1 \leq i \leq N} \mathcal{A}_i(t) \neq \emptyset \quad (\mathcal{A}_i(t) := \mathcal{A}_{x_{i0}}(t))$$

- Solution requires solving large set of coupled polynomial equations and inequalities
- Computation cannot be distributed between the agents

**Helly's theorem** comes to the rescue

Let  $F$  be a finite family of **convex sets** in  $\mathbb{R}^n$ , containing **at least  $n+1$  elements**. **If every  $n+1$  sets of  $F$  have a point in common, then all the sets of  $F$  have a point in common.**

# Parallel Computation

$\bar{t}_{ijk}$ : Minimum time to consensus for agents  $\{a_i, a_j, a_k\}$

Lemma:  $\bar{t} = \max_{1 \leq i, j, k \leq N} \bar{t}_{ijk}$

Theorem:

*Let  $\{a_p, a_q, a_r\}$  be the triple of agents such that  $\bar{t}_{pqr} = \max_{1 \leq i, j, k \leq N} \bar{t}_{ijk}$ . Then the minimum time to consensus  $\bar{t} = \bar{t}_{pqr}$  and the corresponding consensus point  $\bar{X} = \bar{X}_{pqr}$ .*

This means:

- We have to check  ${}^N C_3$  combinations for the max.
- But each of these computations are decoupled from the other – can be distributed between the agents

# Two ways to three agent consensus

**Case 1:**  $\bar{t}_{ijk} = \bar{t}_{ij} = \max\{\bar{t}_{ij}, \bar{t}_{jk}, \bar{t}_{ik}\}$  i.e  
 $\bar{x}_{ij} \in \mathcal{A}_k(\bar{t}_{ij})$

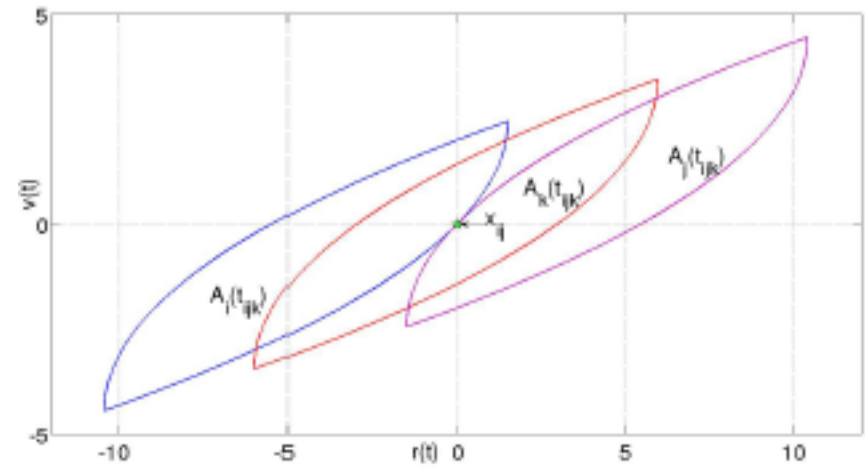
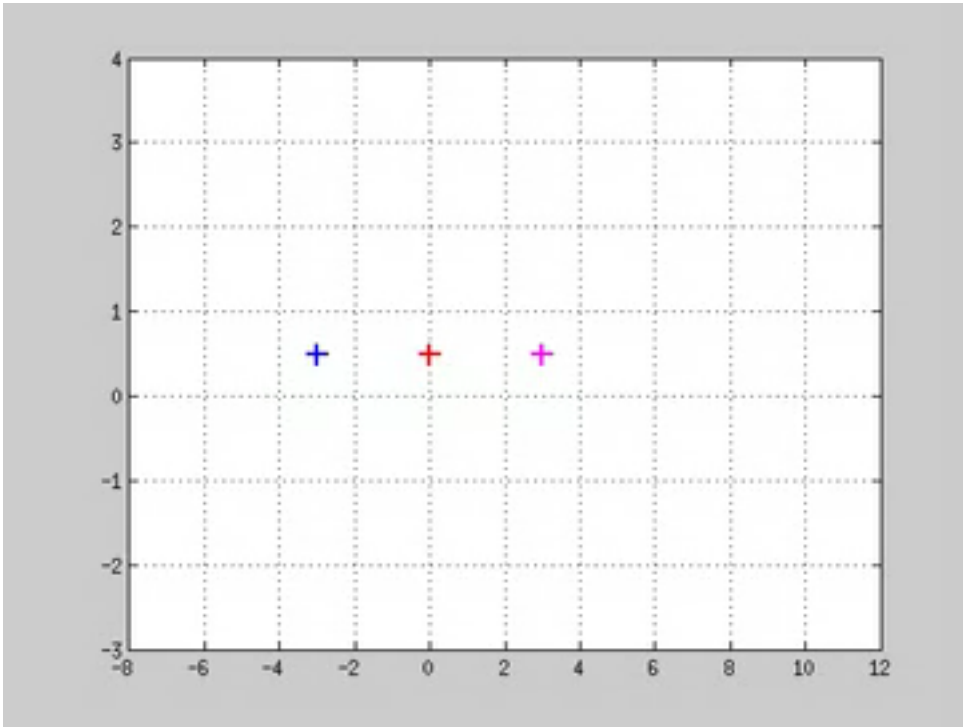
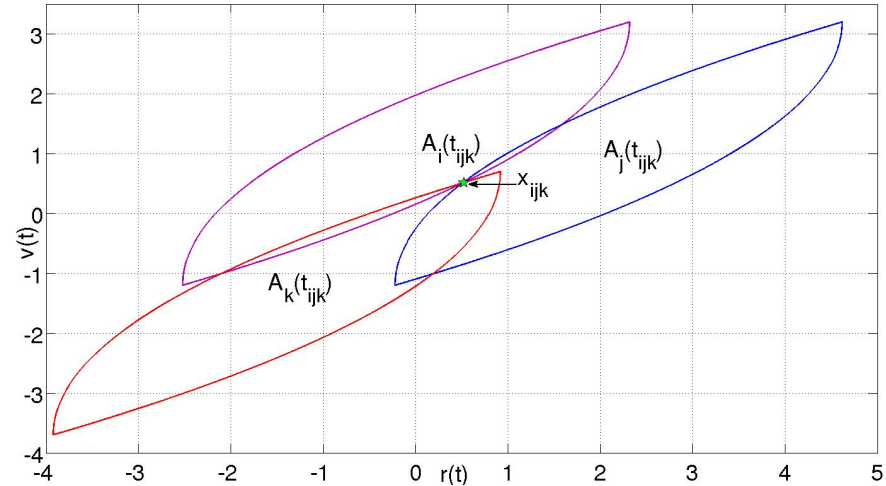
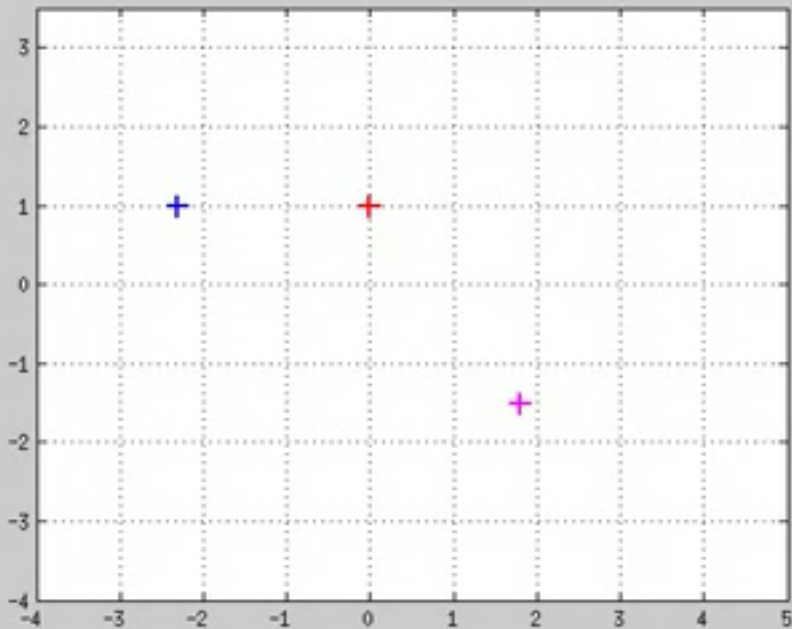


Figure : Case 1

# Two ways to three agent consensus

Case 2:  $\bar{t}_{ijk} > \max\{\bar{t}_{ij}, \bar{t}_{jk}, \bar{t}_{ik}\}$  i.e.  $\bar{x}_{ij} \notin \mathcal{A}_k(\bar{t}_{ij})$

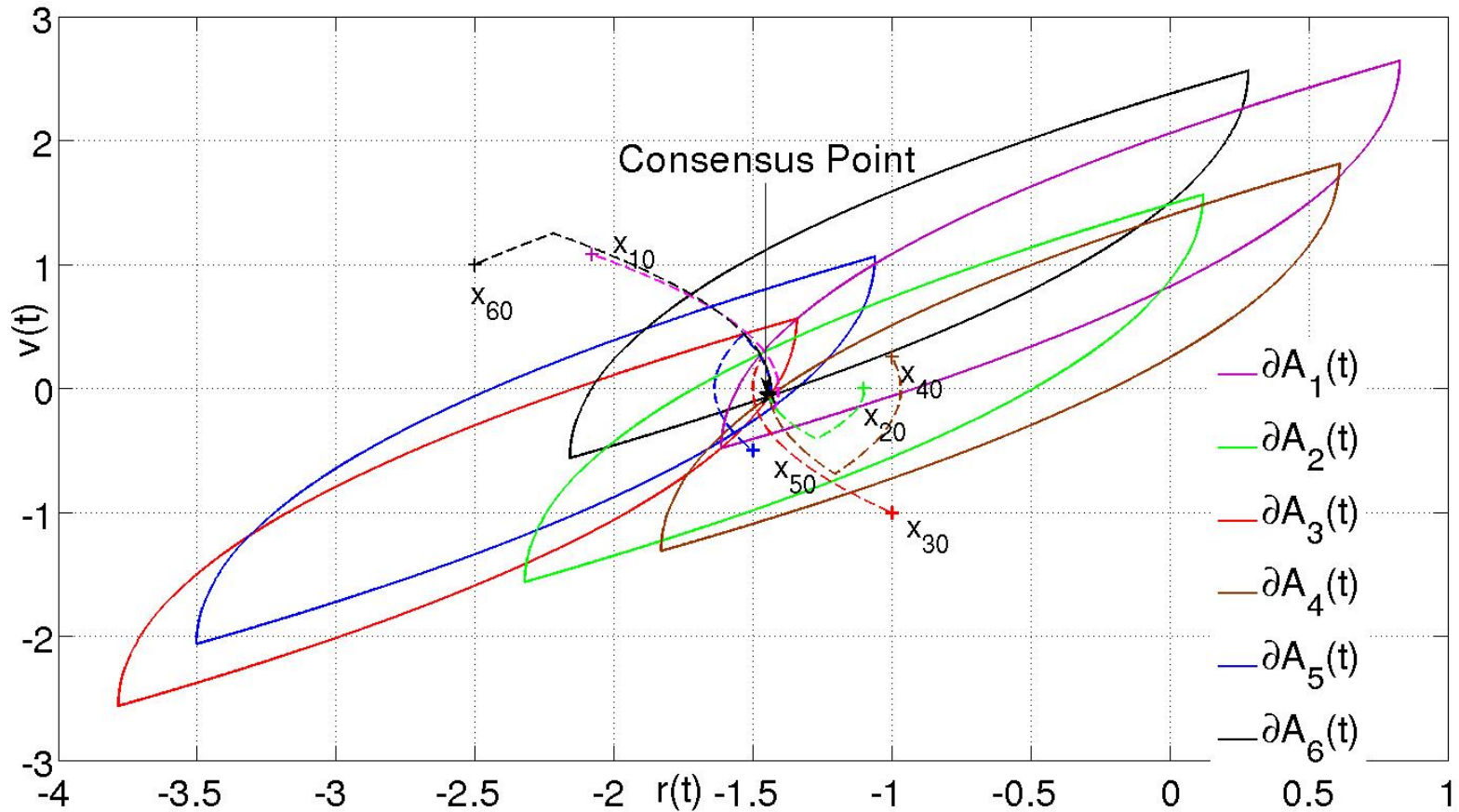




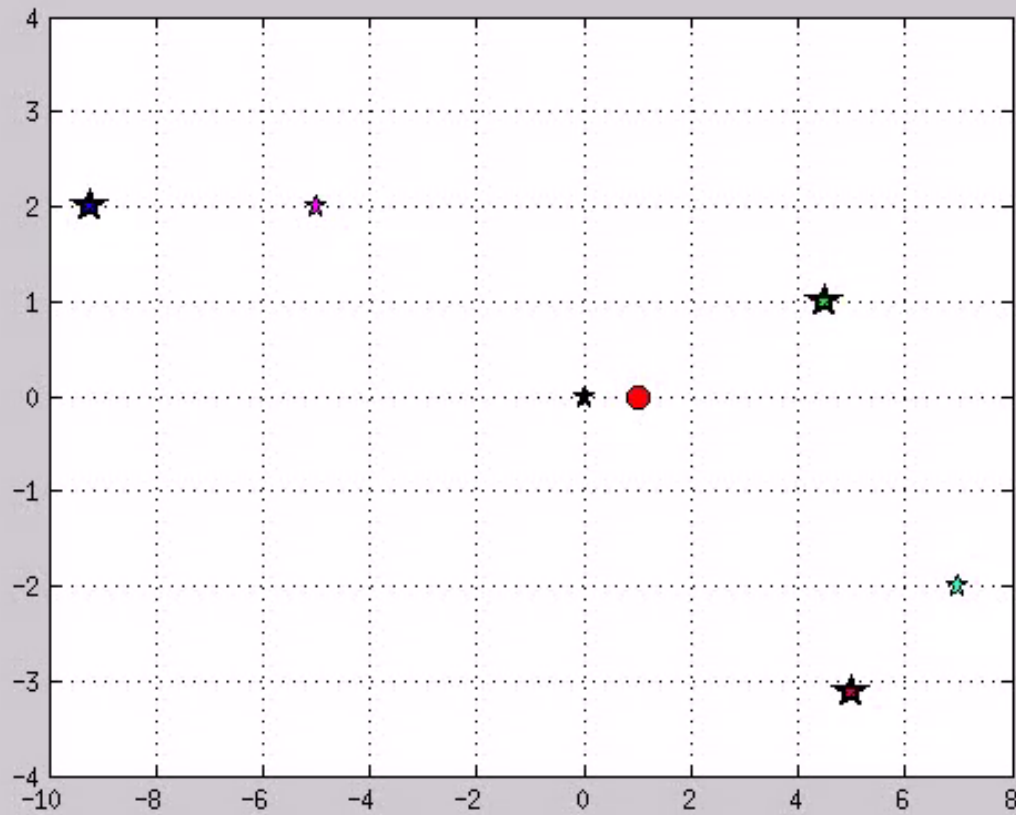
# Computation

- Algebraic formula for computation in both cases have been derived.
- Can be used to directly compute the min time and the consensus point based on the current states
- Proposed algorithm can handle disturbances to the agents by dynamically (feedback) re-computing the target point
  - Then full computation ( ${}^N C_3/N$ ) needs to be done only once at the beginning

# Six agents min time consensus

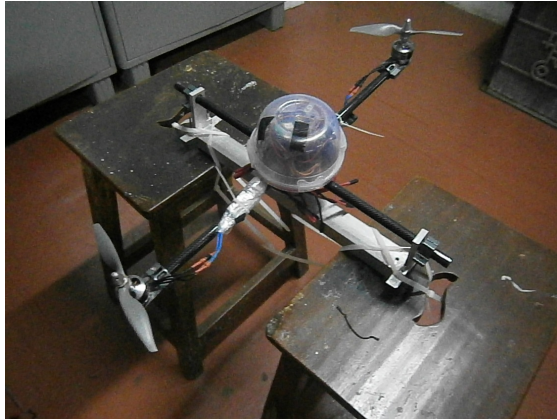


# Min time consensus on $\mathbb{R}^1$

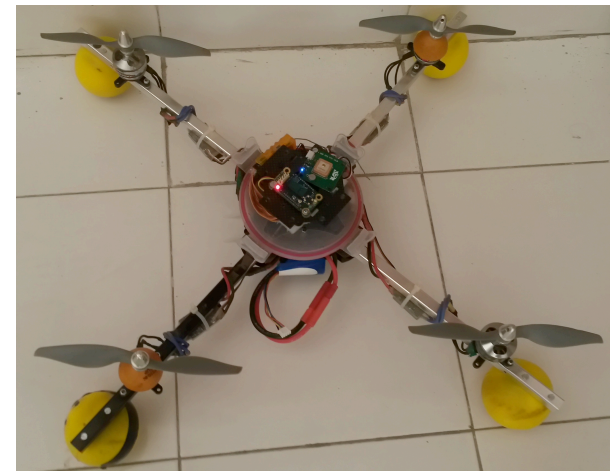
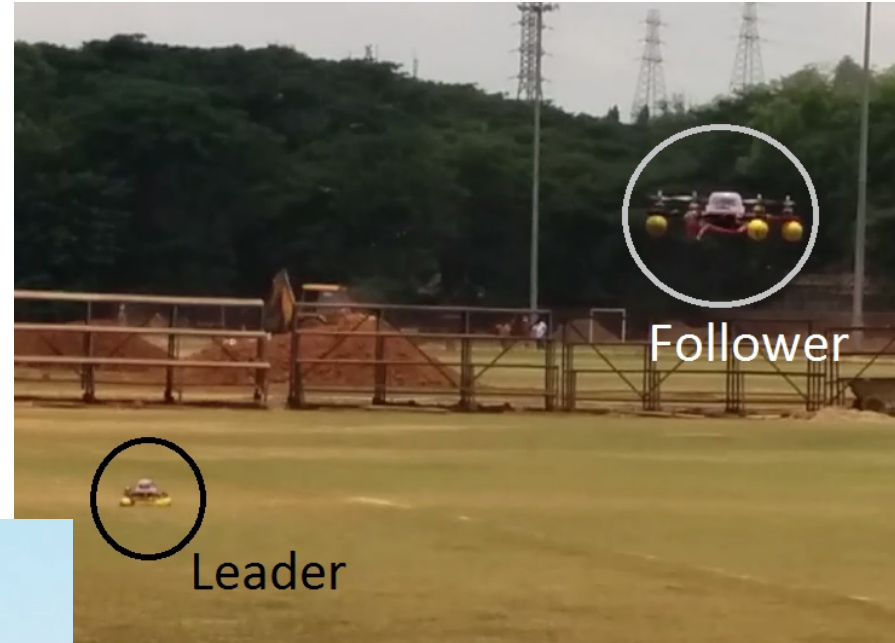


Anything useful?

# Quadcopter testbed

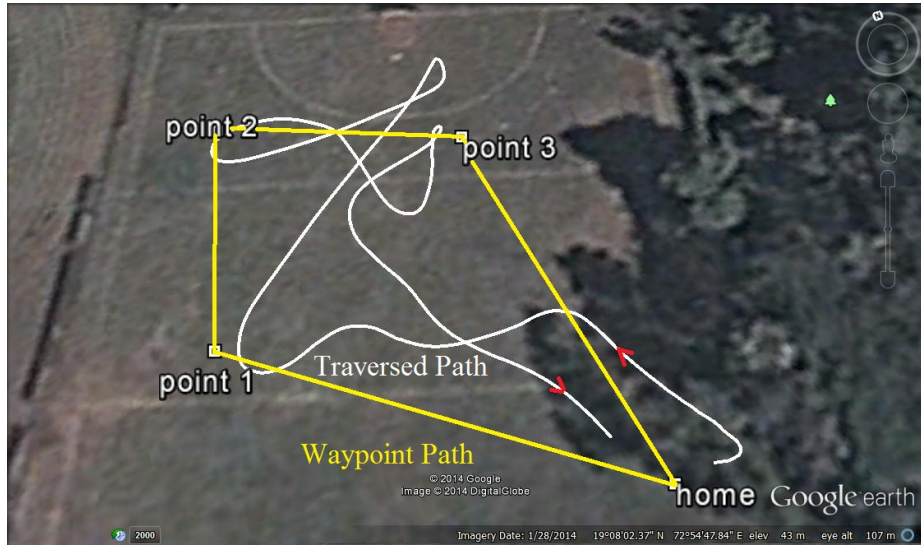


2012



2012

# GPS waypoint-Leader Follower



2013

2013

2014



# Video: Leader Follower - 1



# Video: Leader Follower - 2



**Still a long way to go before we can catch up with the leopard, duck or even cows**



Thank You