STARMAC 2
Quadrotor Helicopters

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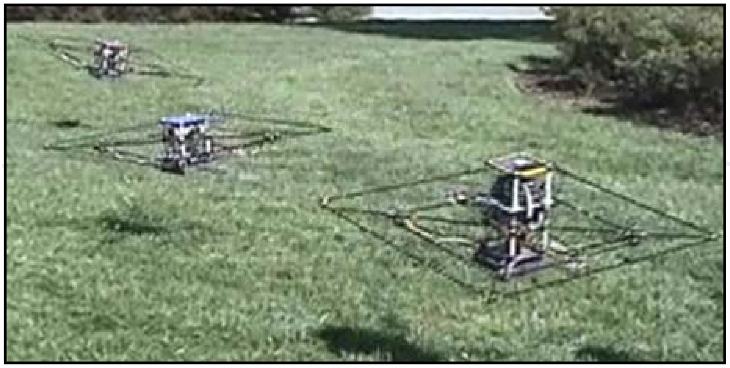
Mobile Sensor Network Control

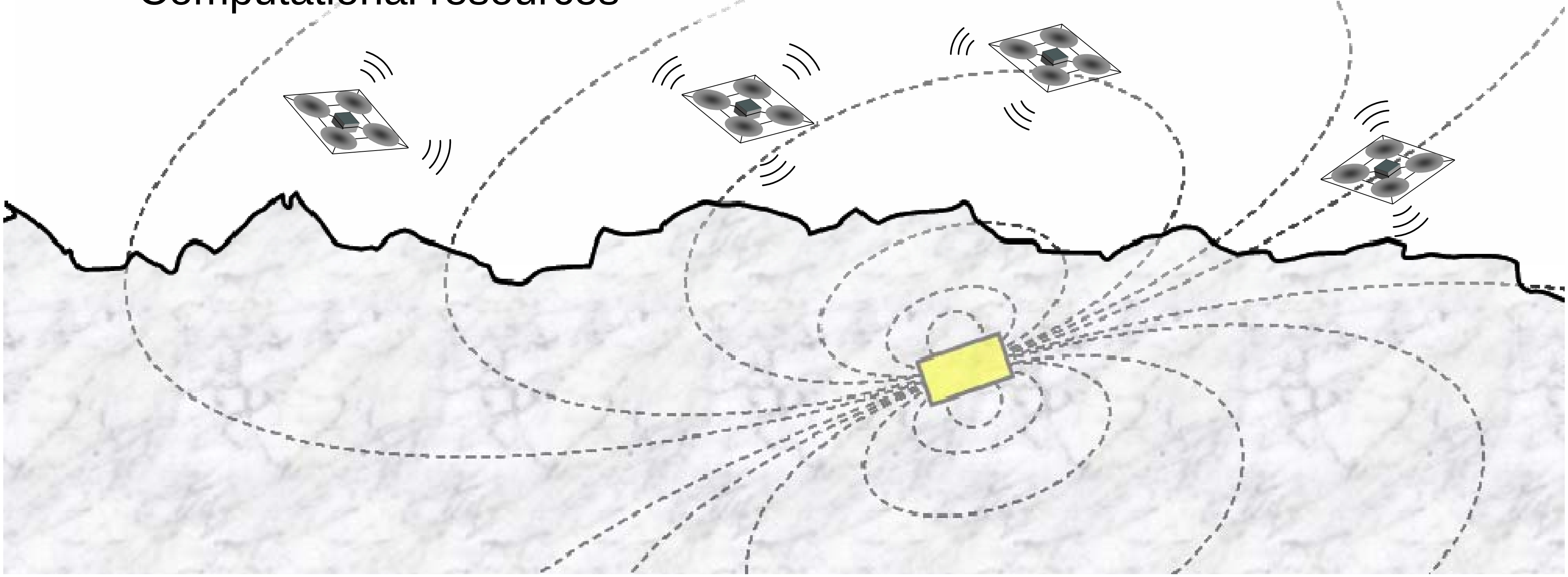
Control Objectives:

- Automatic information gathering
- Safe interaction

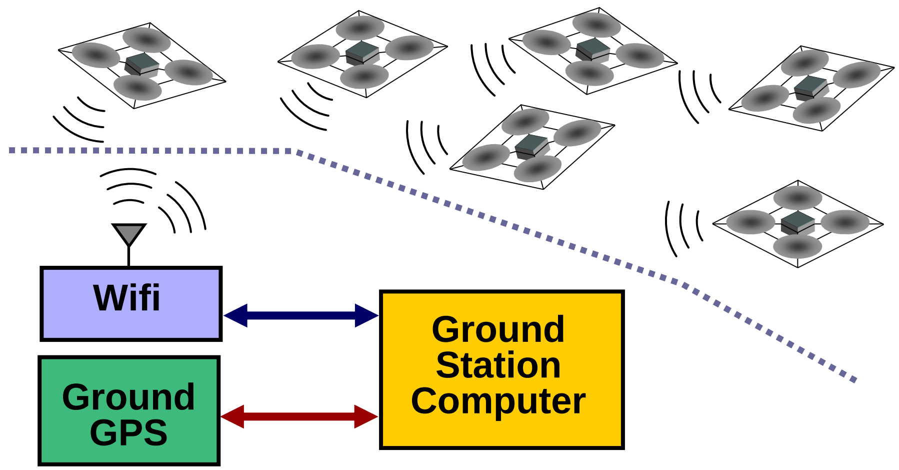


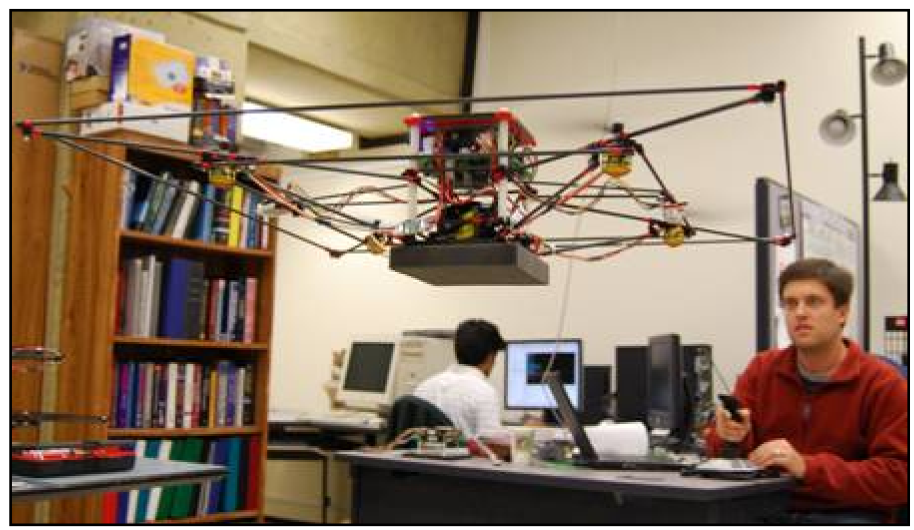
Constraints:

- Power budget
- Communication bandwidth
- Computational resources



STARMAC System

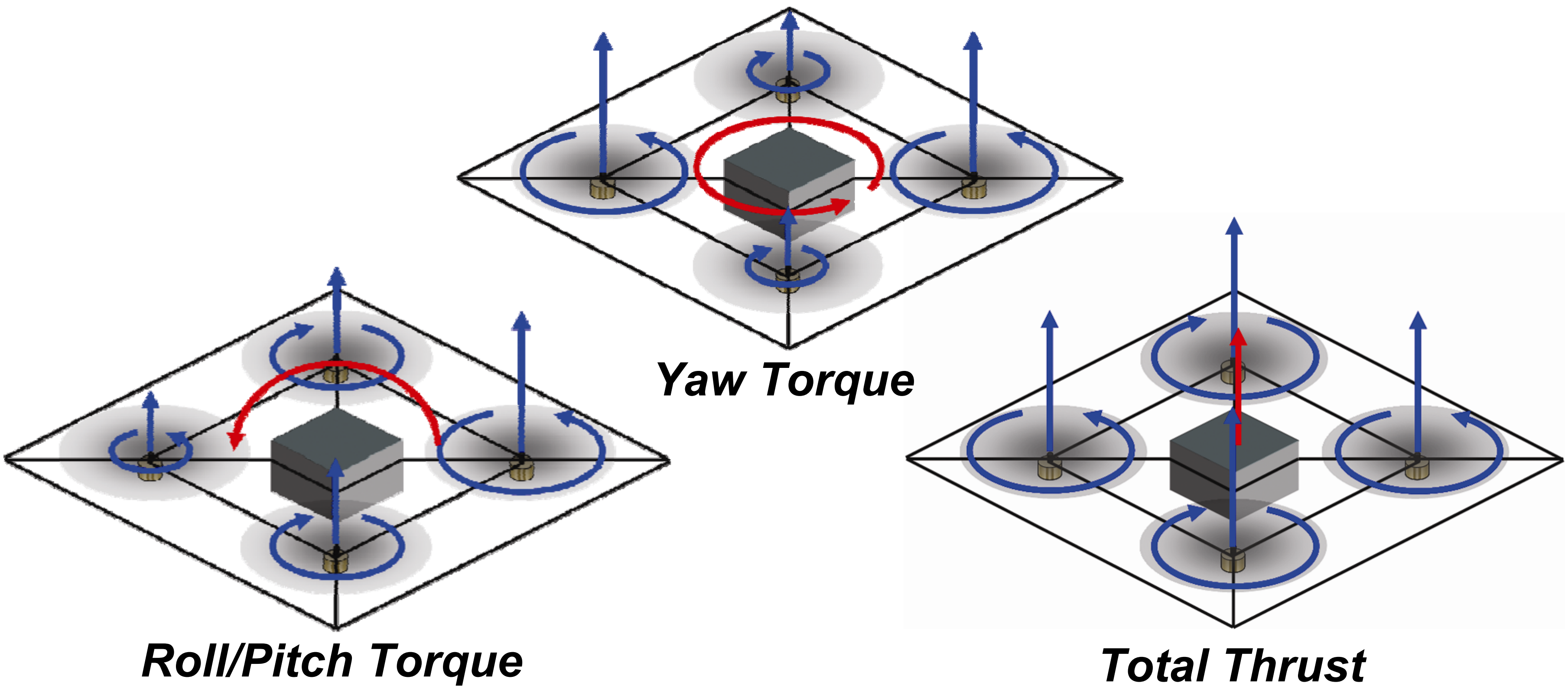




- Self Sufficient UAVs
  - Onboard computation
  - Onboard sensing
- Real Time Execution
  - Estimation
  - Control

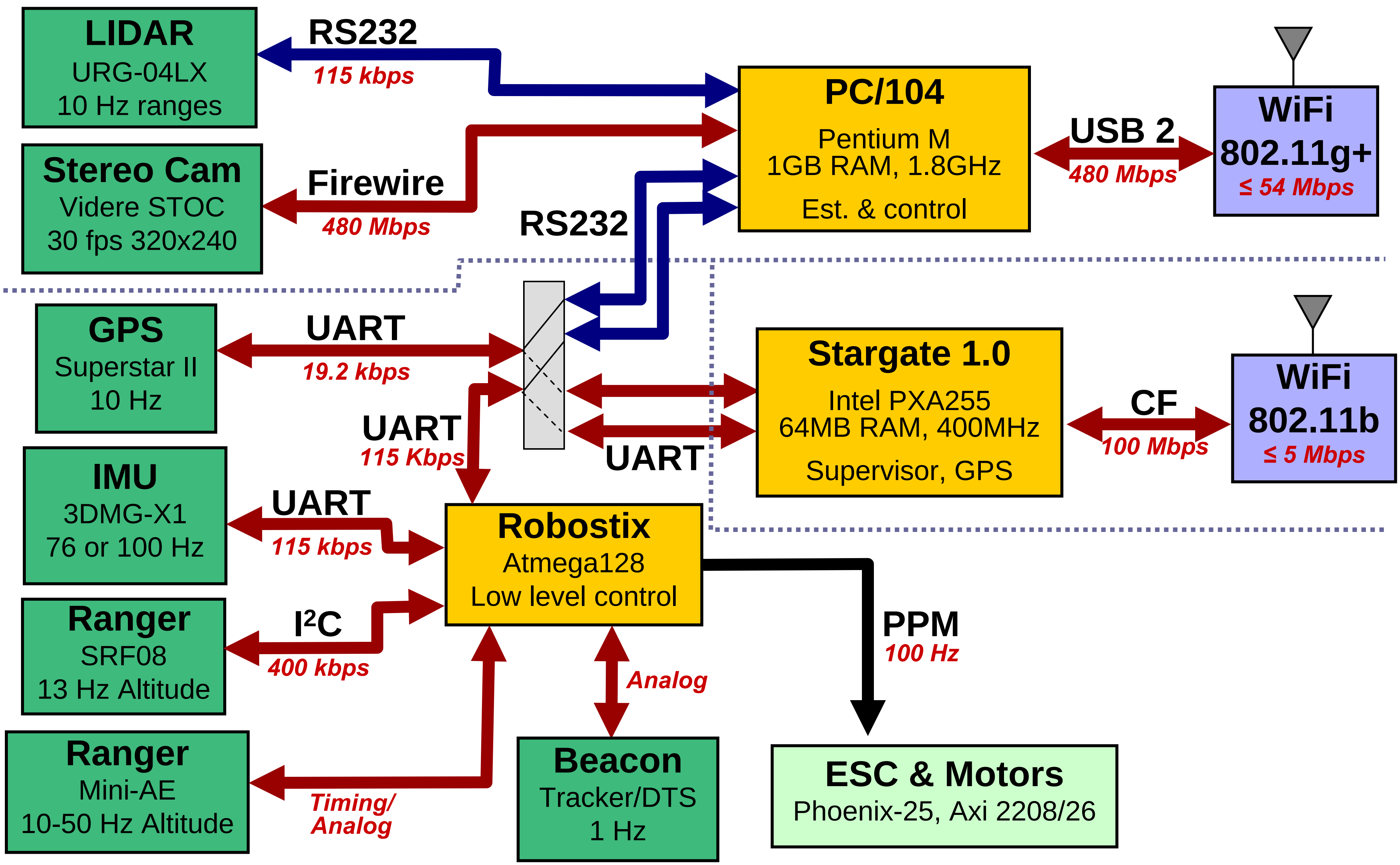
Quadrotor Helicopter Control

Angular accelerations and vertical acceleration are controlled by varying the propeller speeds.

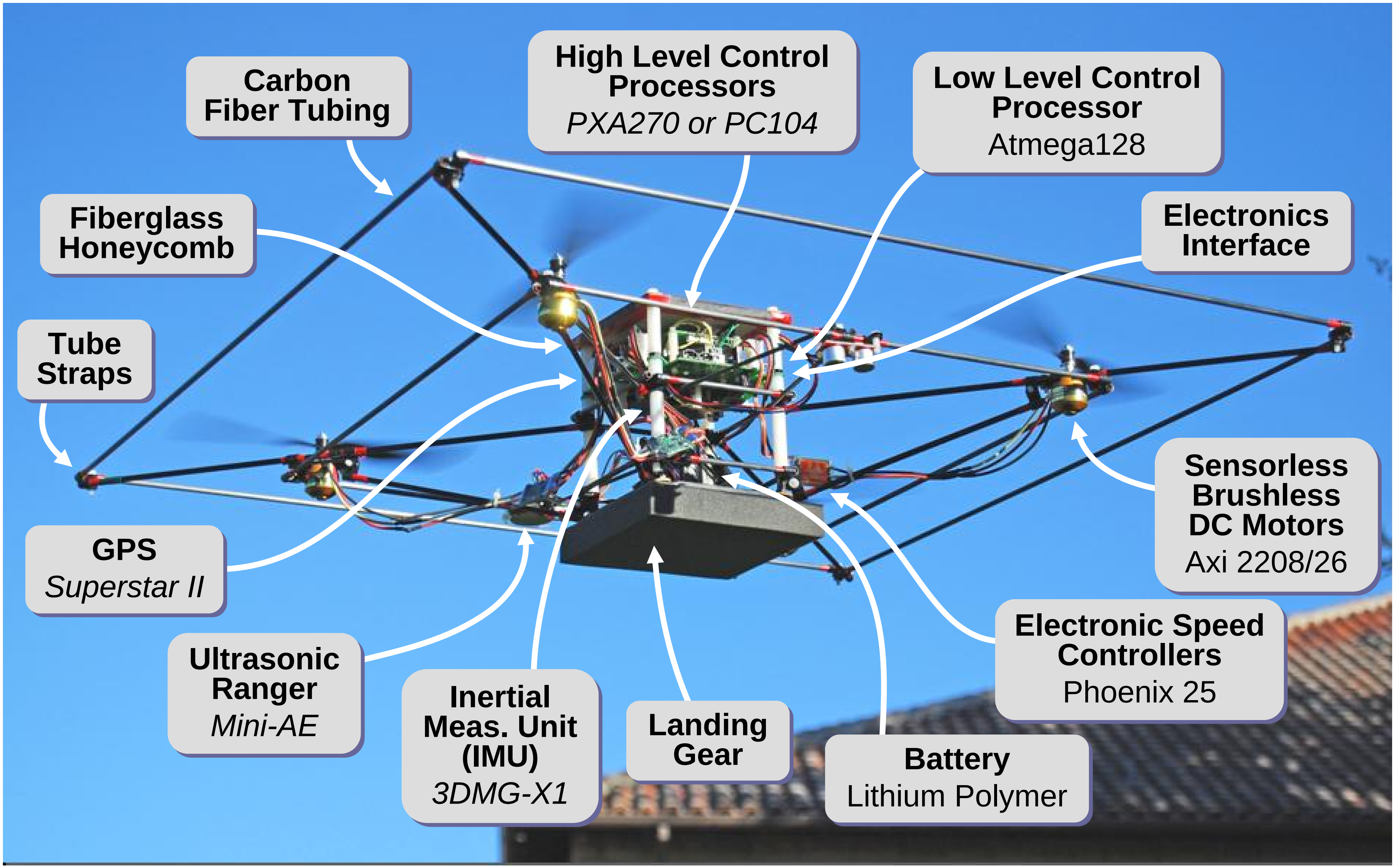


Hoffmann, Huang, Waslander, Tomlin, *AIAA GNC*, 2007

STARMAC 2 Electronics System



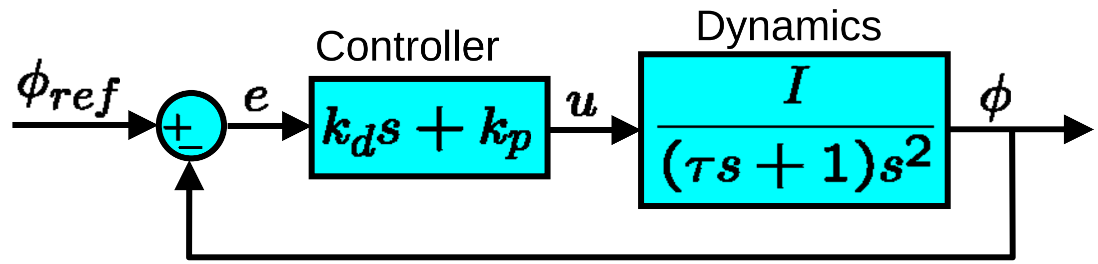
STARMAC 2 Quadrotor Helicopter

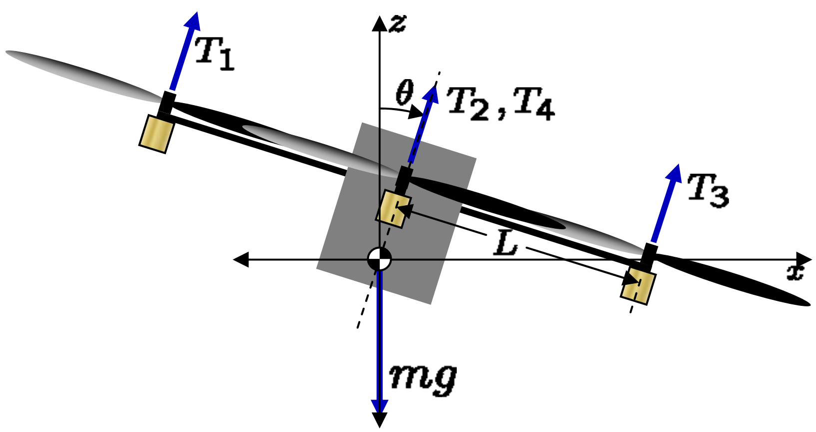


Attitude Control – Dynamic Response

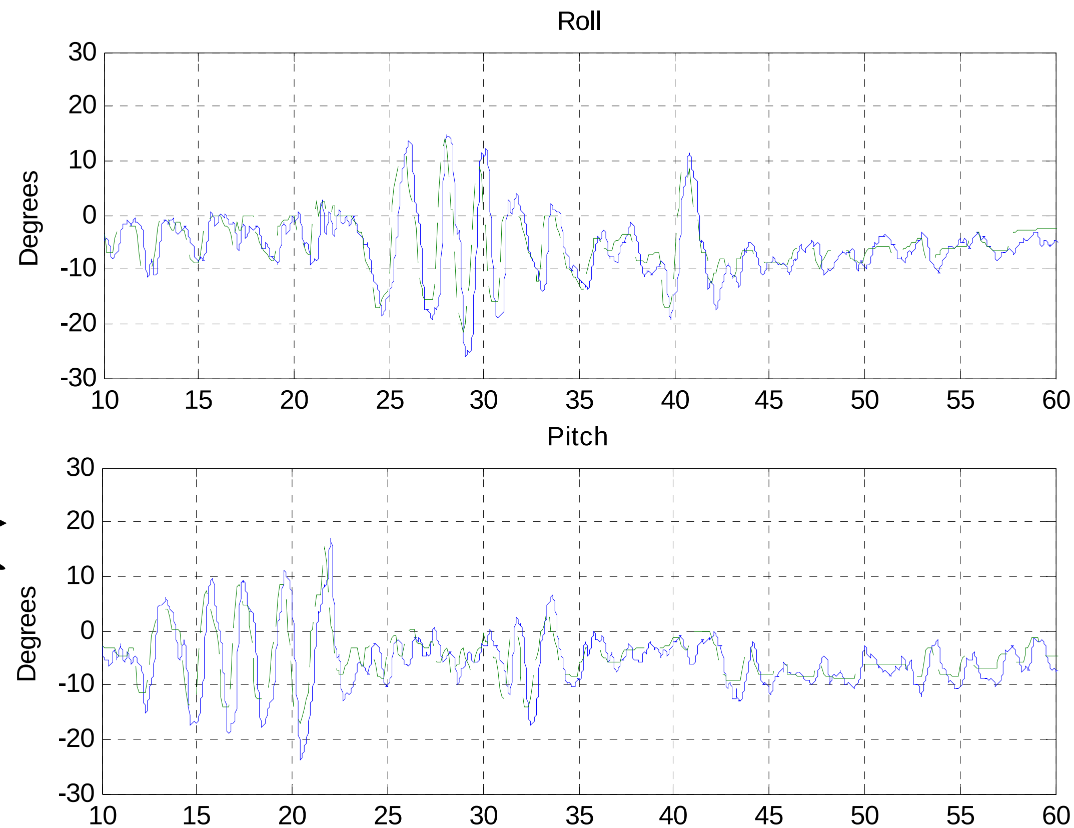
Key Developments

- Rigid Frame
- Rotor Spacing
- Tip Vortex Impingement
- Command Tracking PID
- Digital Input Filter
- 16 bit Resolution

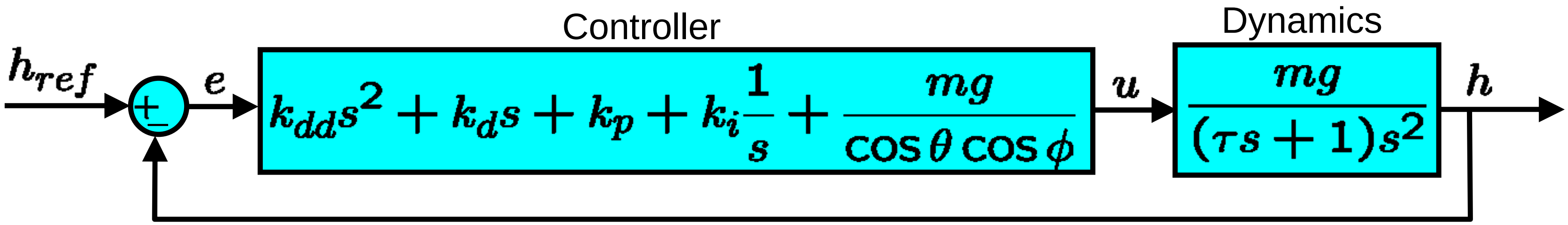




$$u = (T_1 - T_3)L$$



Altitude Control



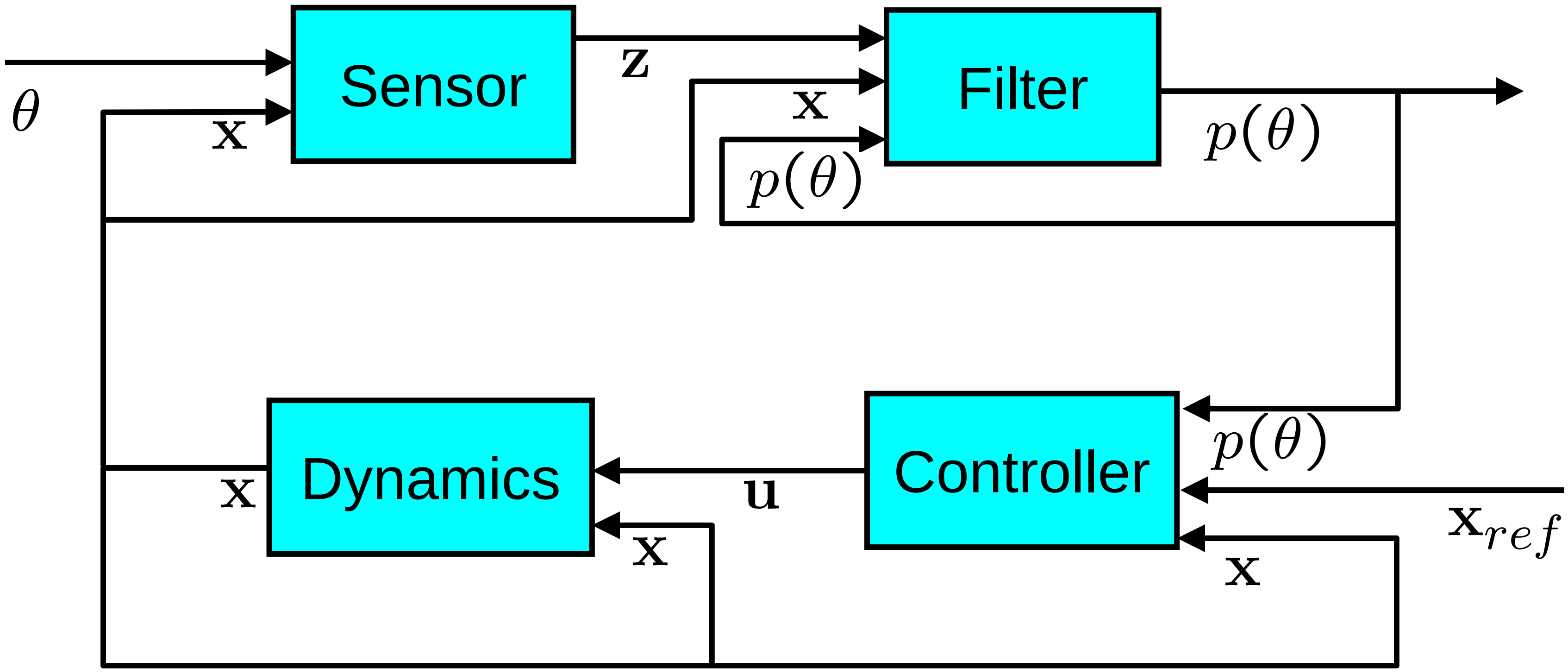
$$u = \sum_{i=1}^{4} T_i$$

Key Developments

- Rotor Spacing
- Tip Vortex Impingement
- Tilt Compensation
- Specific Thrust Control
- Sensor Selection

Flight Tests

Information-Seeking Problem Framework



- Controller goal is to minimize the uncertainty of $p(\theta)$
- There may be *no reason* to move towards the target

Modeling Uncertainty to Increase Knowledge

Target State: θ
Observations: $\mathbf{z}_{t+1}$
Target State Model: $p(\theta)$

Vehicle States: $\mathbf{x}_t$
Control Inputs: $\mathbf{u}_t$
Motion Model: $\mathbf{x}_{t+1} = f(\mathbf{x}_t, \mathbf{u}_t)$

Sensor model: $p(\mathbf{z}_{t+1}|\theta; \mathbf{x}_{t+1})$

Use Bayes' Rule to update the target state model,

$$p(\theta|\mathbf{z}_{t+1}; \mathbf{x}_{t+1}) = \frac{p(\theta)p(\mathbf{z}_{t+1}|\theta; \mathbf{x}_{t+1})}{p(\mathbf{z}_{t+1}; \mathbf{x}_{t+1})}$$

Minimize the expected future uncertainty,

$$H(\theta|\mathbf{z}_{t+1}) = H(\theta) - I(\theta; \mathbf{z}_{t+1})$$

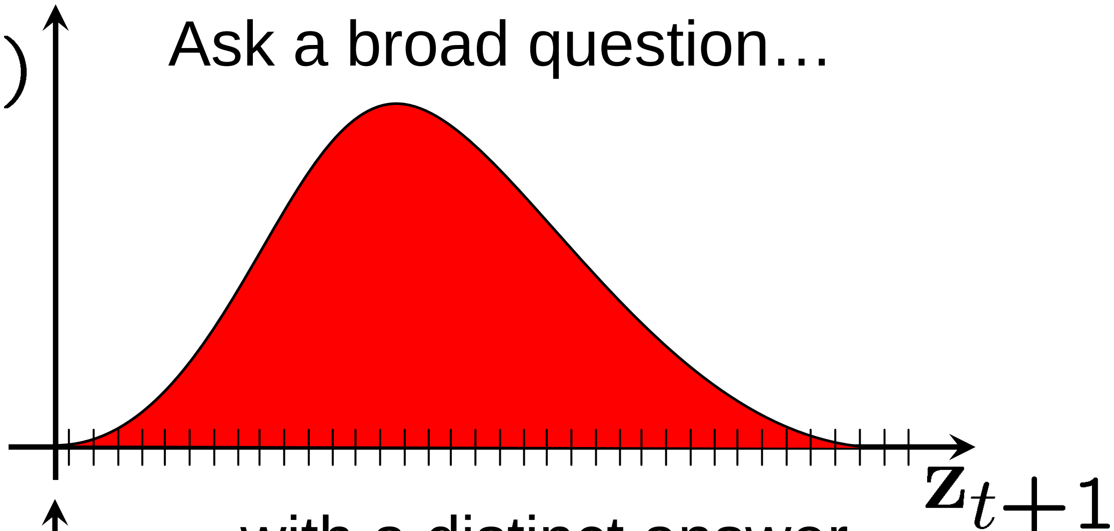
Maximizing Information

$$\boxed{I(\mathbf{z}_{t+1};\theta_t^{(i)}) = H(\mathbf{z}_{t+1}) - H(\mathbf{z}_{t+1}|\theta_t^{(i)})}$$

$p(\mathbf{z}_{t+1};\mathbf{x}_{t+1})$

Expected Observation Probability

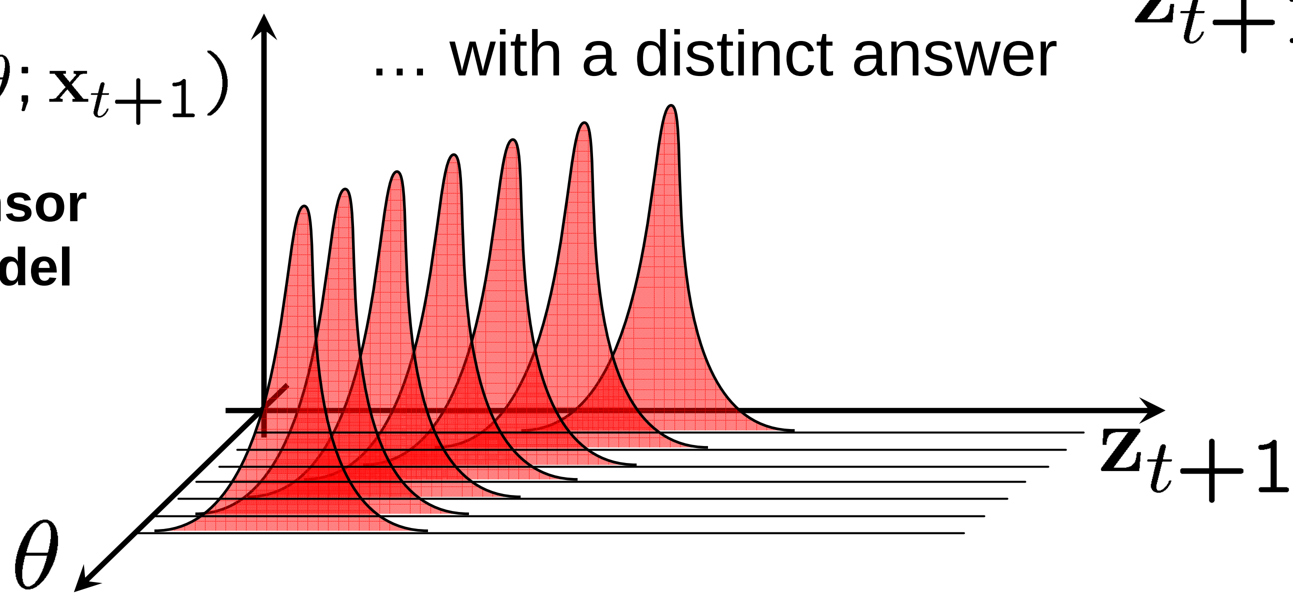
Ask a broad question…



$p(\mathbf{z}_{t+1}|\theta;\mathbf{x}_{t+1})$

Sensor Model

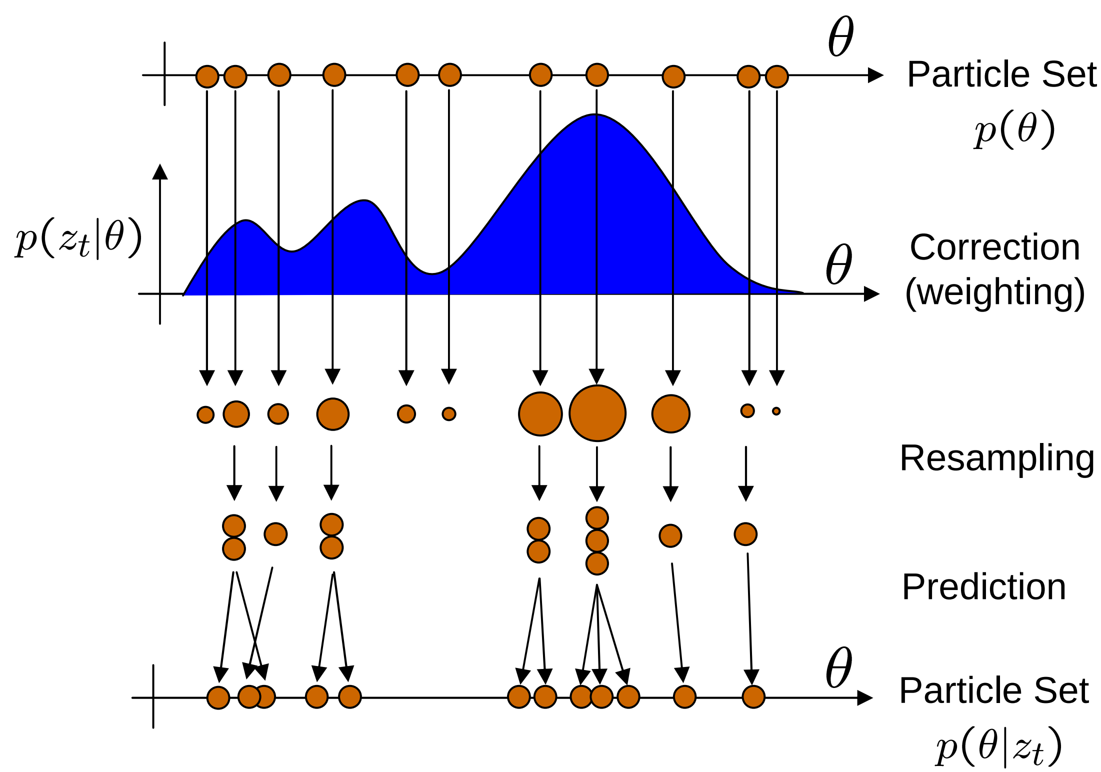
… with a distinct answer



Bayes' Rule using Particle Filters

$$p(\theta|\mathbf{z}_{t+1};\mathbf{x}_{t+1}) = \frac{p(\theta)p(\mathbf{z}_{t+1}|\theta;\mathbf{x}_{t+1})}{p(\mathbf{z}_{t+1};\mathbf{x}_{t+1})}$$

- Uses available prior knowledge
- Allows multimodal posterior
- Permits nonlinear & non-Gaussian models



Mutual Information from Particle Filters

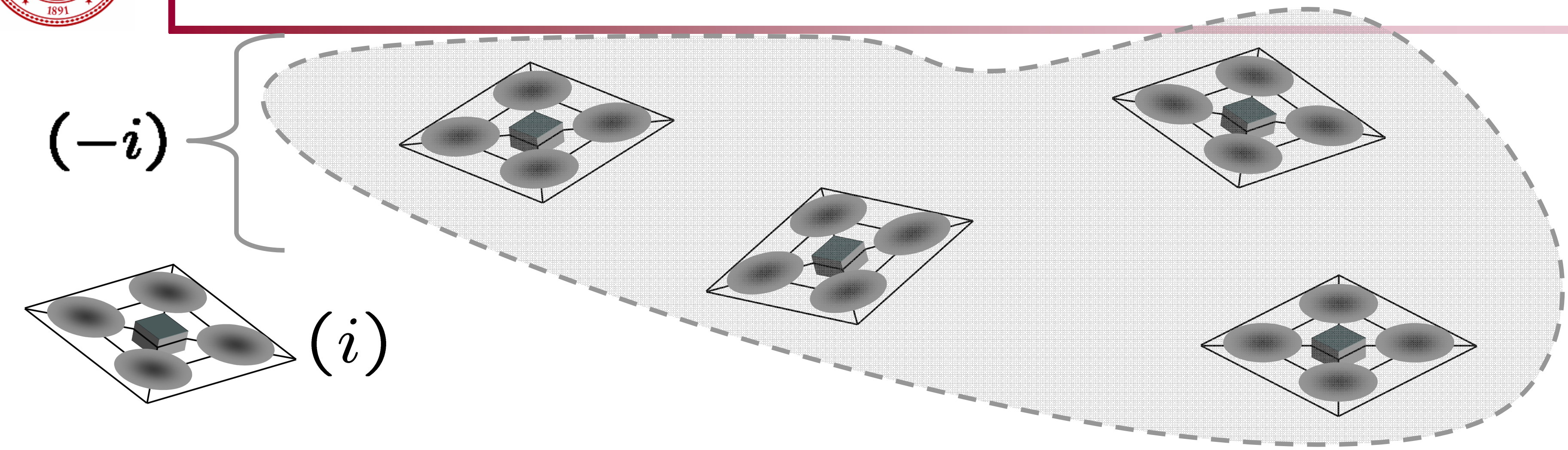
$$\underbrace{I(\mathbf{z}_{t+1};\theta_t^{(i)})}_{\substack{\text{observation}\\\text{information}}} = \underbrace{H(\mathbf{z}_{t+1})}_{\substack{\text{observation}\\\text{uncertainty}}} - \underbrace{H(\mathbf{z}_{t+1}|\theta_t^{(i)})}_{\substack{\text{conditional}\\\text{observation uncertainty}}}$$

$$H(\mathbf{z}_{t+1}) \approx$$
$$-\int_Z \left\{ \left(\sum_{k=1}^{N} \left(\mathbf{w}_{t,k}^{(i)} \prod_{j=1}^{n_v} p_{t+1|t}(\mathbf{z}^{(j)}|\theta^{(i)}=\tilde{\theta}_{t,k}^{(i)};\mathbf{u}_t,\mathbf{x}_t) \right) \right) \right.$$
$$\left. \cdot \log \left(\sum_{k=1}^{N} \left(\mathbf{w}_{t,k}^{(i)} \prod_{j=1}^{n_v} p_{t+1|t}(\mathbf{z}^{(j)}|\theta^{(i)}=\tilde{\theta}_{t,k}^{(i)};\mathbf{u}_t,\mathbf{x}_t) \right) \right) \right\} d\mathbf{z}$$

$$H(\mathbf{z}_{t+1}|\theta_t^{(i)}) \approx$$
$$-\int_Z \sum_{k=1}^{N} \left\{ \mathbf{w}_{t,k}^{(i)} \prod_{j=1}^{n_v} p_{t+1|t}(\mathbf{z}^{(j)}|\theta^{(i)}=\tilde{\theta}_{t,k}^{(i)};\mathbf{u}_t,\mathbf{x}_t) \right.$$
$$\left. \cdot \log \prod_{j=1}^{n_v} p_{t+1|t}(\mathbf{z}^{(j)}|\theta^{(i)}=\tilde{\theta}_{t,k}^{(i)};\mathbf{u}_t,\mathbf{x}_t) \right\} d\mathbf{z}$$

Hoffmann, Waslander, Tomlin, *GNC*, 2006

Distributed Optimization Program



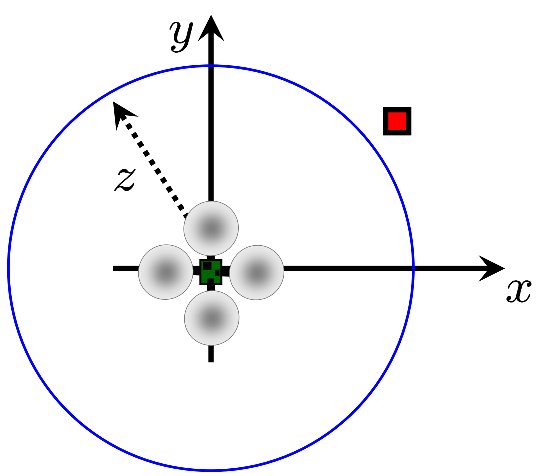
$$\underset{\mathbf{u}_t^{(i)} \in U^{(i)}}{\text{minimize}} \quad -I^{(i)}(\mathbf{x}_t^{(i)}, \mathbf{u}_t^{(i)}, \theta_t^{(i)} | \mathbf{x}_t^{(-i)}, \mathbf{u}_t^{(-i)}) + \frac{1}{\beta} P(\mathbf{x}_t^{(i)}, \mathbf{u}_t^{(i)} | \mathbf{x}_t^{(-i)}, \mathbf{u}_t^{(-i)})$$

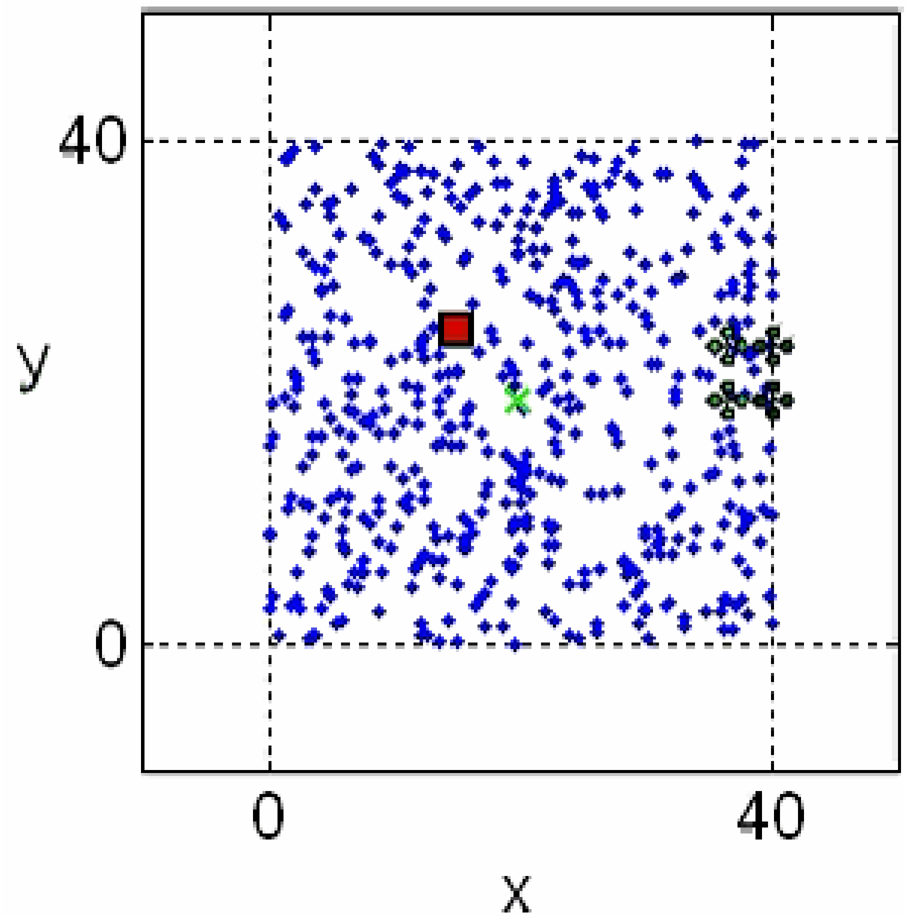
$$\text{subject to} \quad \begin{aligned} \mathbf{x}_{t+1}^{(i)} &= f_t^{(i)}(\mathbf{x}_t^{(i)}, \mathbf{u}_t^{(i)}) \\ \mathbf{z}_{t+1}^{(i)} &= h_t^{(i)}(\mathbf{x}_{t+1}^{(i)}, \theta_t^{(i)}, \eta_t^{(i)}) \end{aligned}$$

Ihalhan, Stipanovic, Tomlin, *CDC*, 2002 **Hoffmann, Waslander, Tomlin, *CDC, 2006***

Range-Only Example

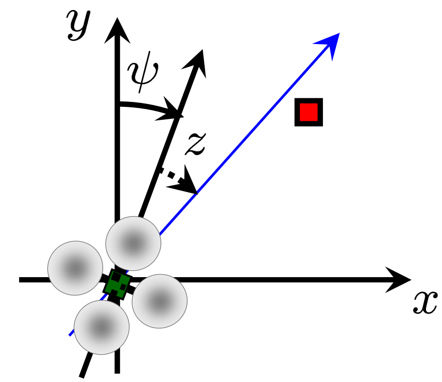
Measure the distance to the target



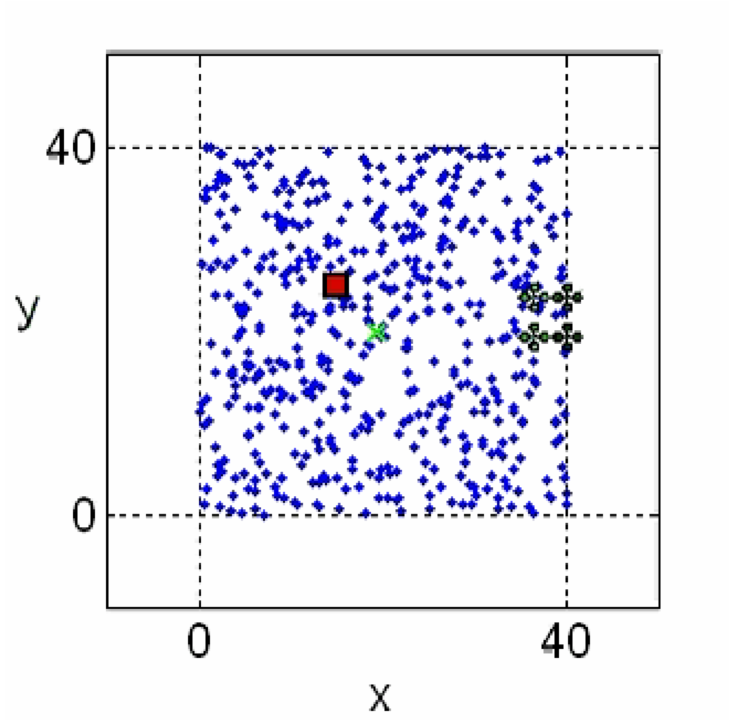


Bearings-Only Example

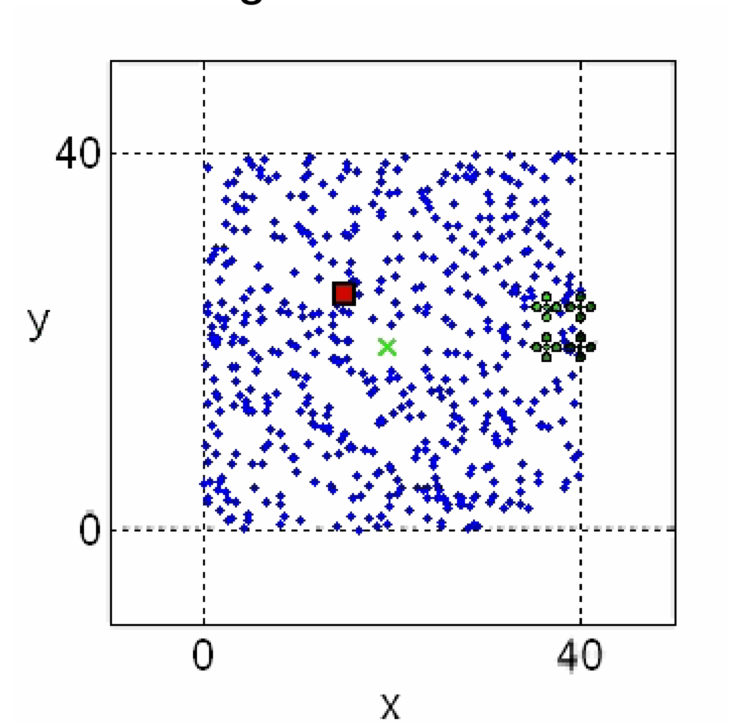
Measure the direction to the target



Medium Noise

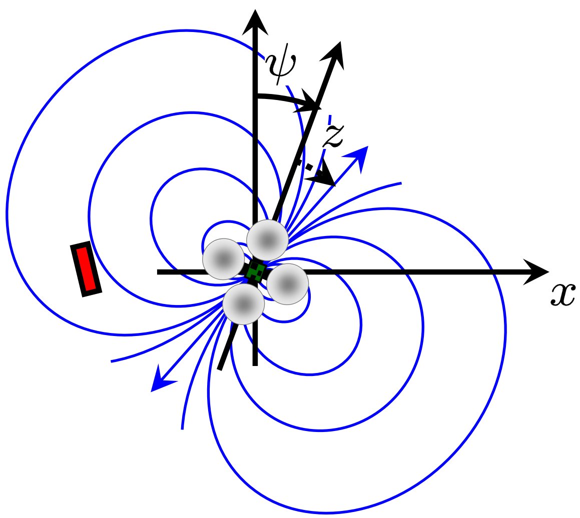


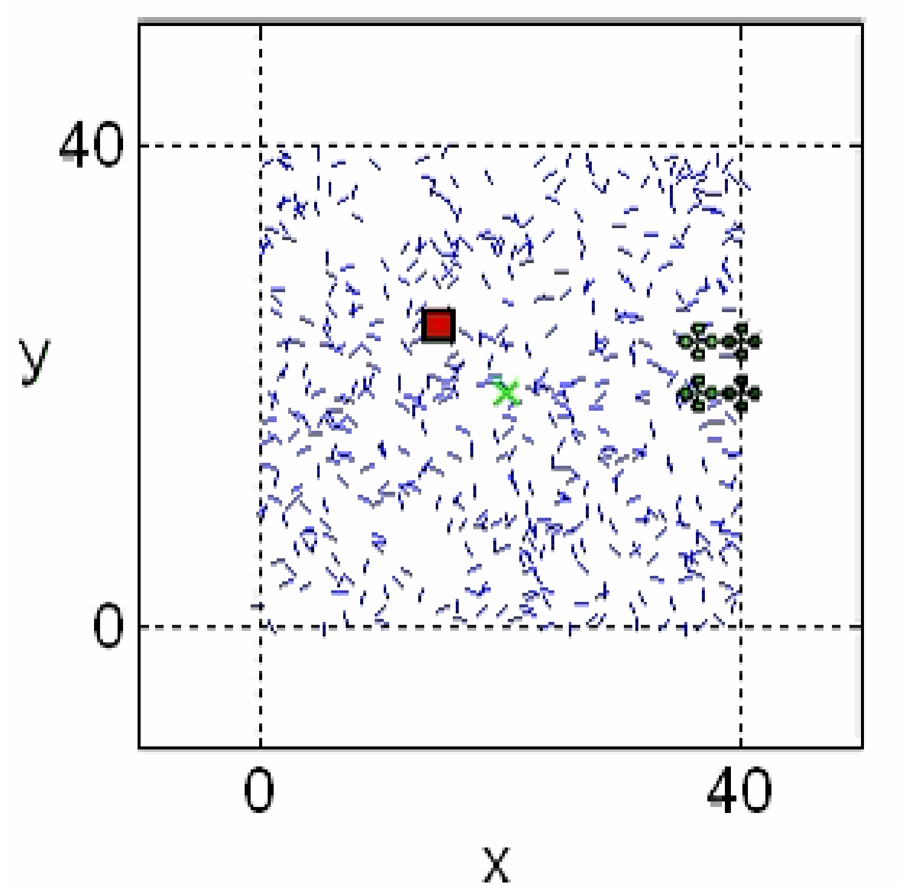
High Noise



Beacon Field Example

Measure the field line orientation





Research Directions

- Flight Tests of Autonomous Search
- Time Horizon, Moving Targets
- Generalize to Other Applications
  - Unexploded ordinance detection
  - Submarine detection
  - Beacon tracking scenarios
  - RFID tracking
  - Survey of disaster areas
  - Biological studies, animal monitoring
  - etc…
- Distributed Concurrent Execution Framework

http://hoffmann.stanford.edu/
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