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Wireless Communication Networks Between Distributed Autonomous Systems Using Self-Tuning Extremum Control

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Wireless Communication Networks Between Distributed Autonomous Systems Using Self-Tuning Extremum Control

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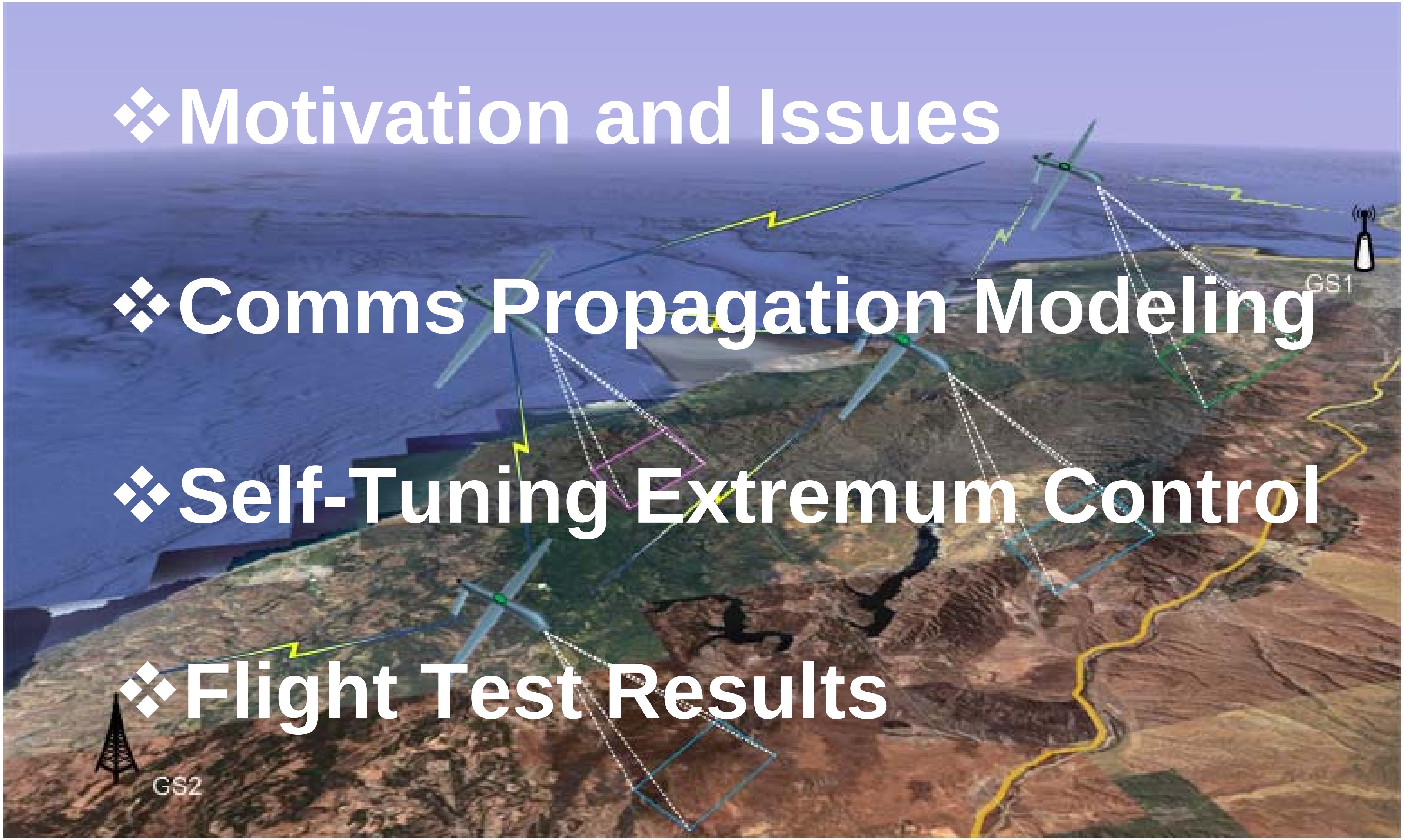
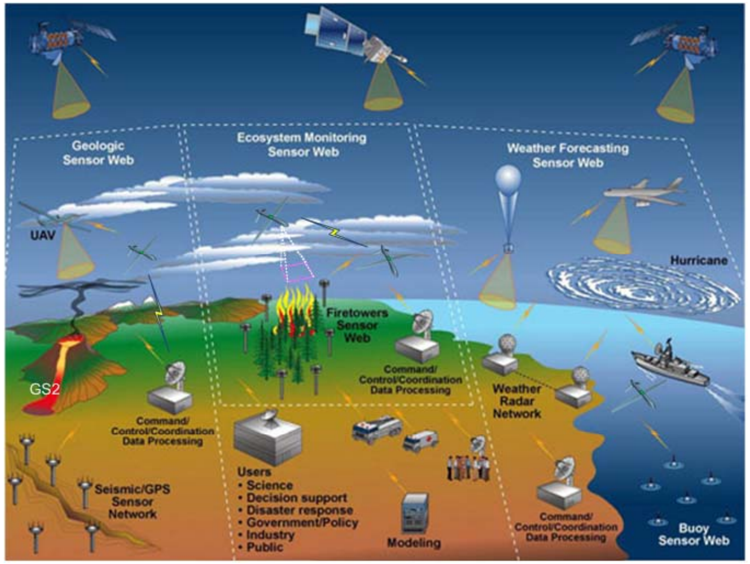
Milestones

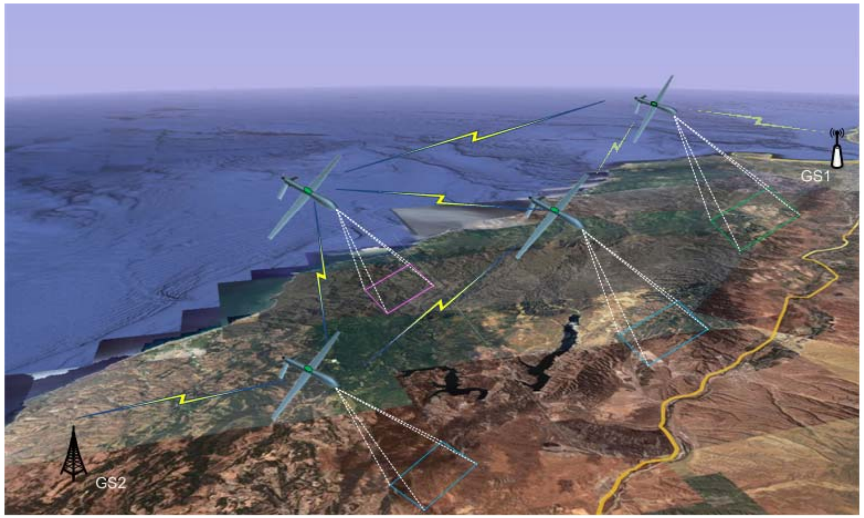


- Motivation and Issues
- Comms Propagation Modeling
- Self-Tuning Extremum Control
- Flight Test Results



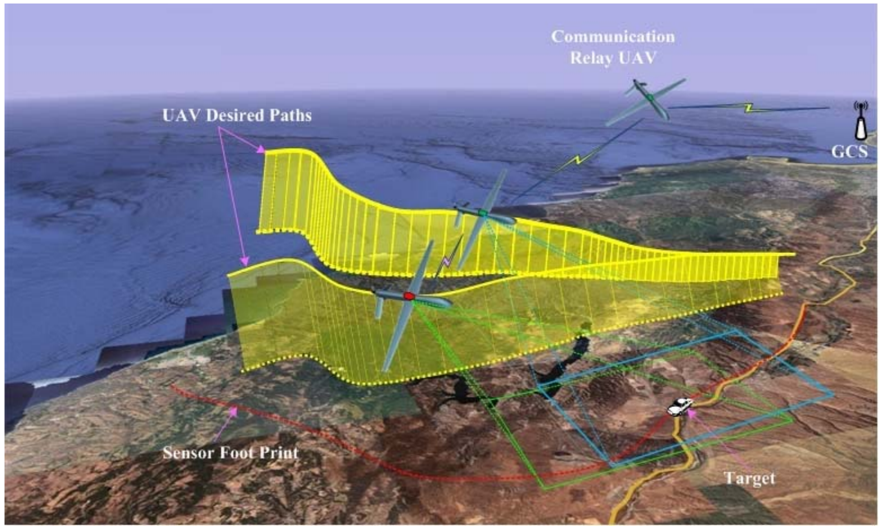
❖Applications

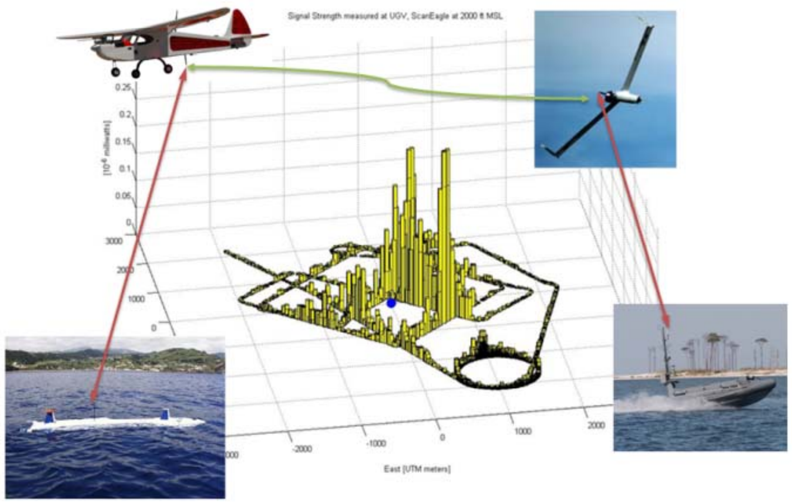
- Nature Monitoring - Civil
  (Disaster, Forest Fire, Weather)
- Surveillance & Coverage - Military
  (SA, Decision Support, ISR)
- Remote Sensing - Science
  (GIS, Ocean Map Building, etc)



❖ Research Goals

- ❑ Dispatch a swarm of networked UAVs as communication relay nodes for real-time decision-making support and situational awareness

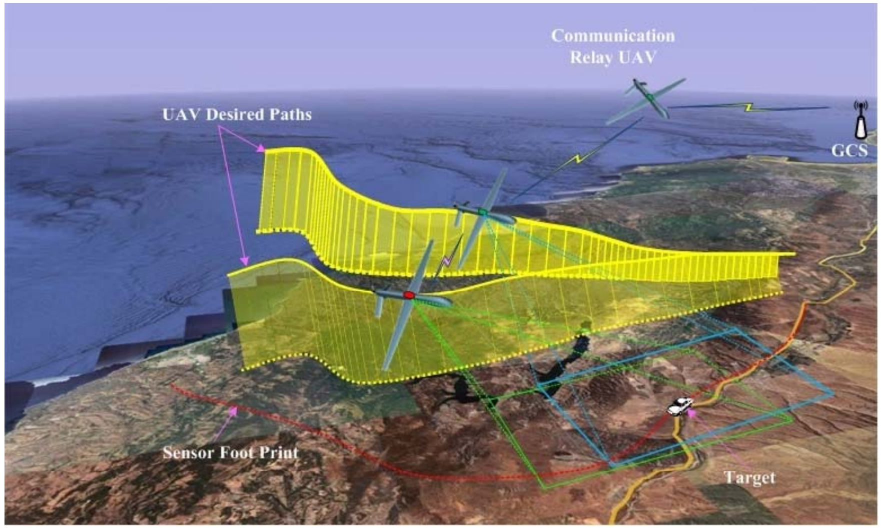


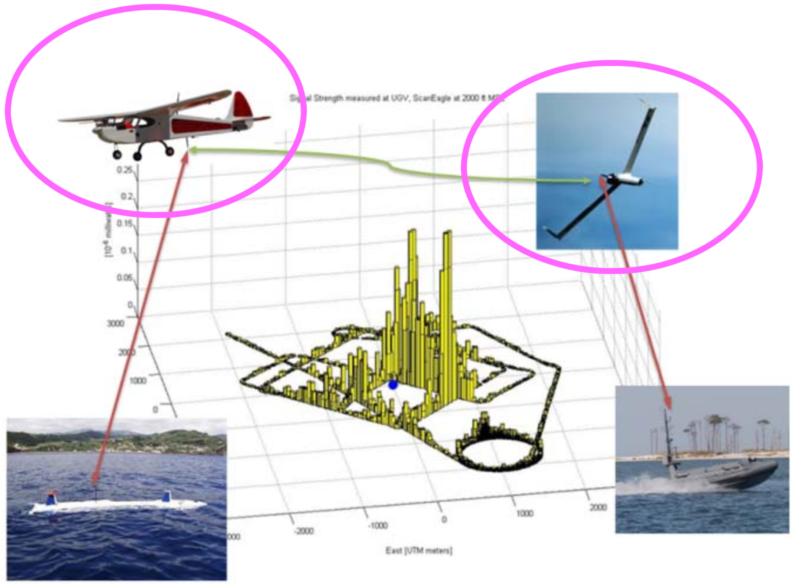


Research Goals & Issues

❖ Research Issues

- ❑ High Bandwidth Communication Links (Max. Throughputs)
- ❑ Wide Area/Range Coverage (Network Coverage Control)
- ❑ Long-Term Communication Relay (Aerial Platforms)

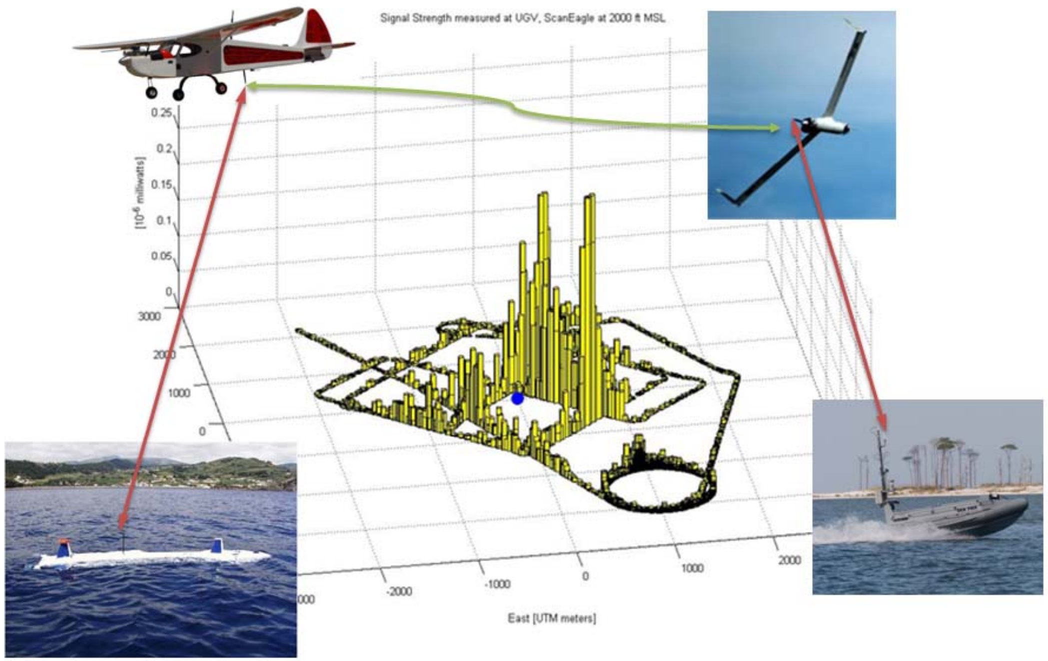




Maximum Comms Networking

❖Objective and Approach

- ❑Develop control algorithms that allow UAVs to reposition themselves autonomously at optimal flight location to maximize the communications link quality

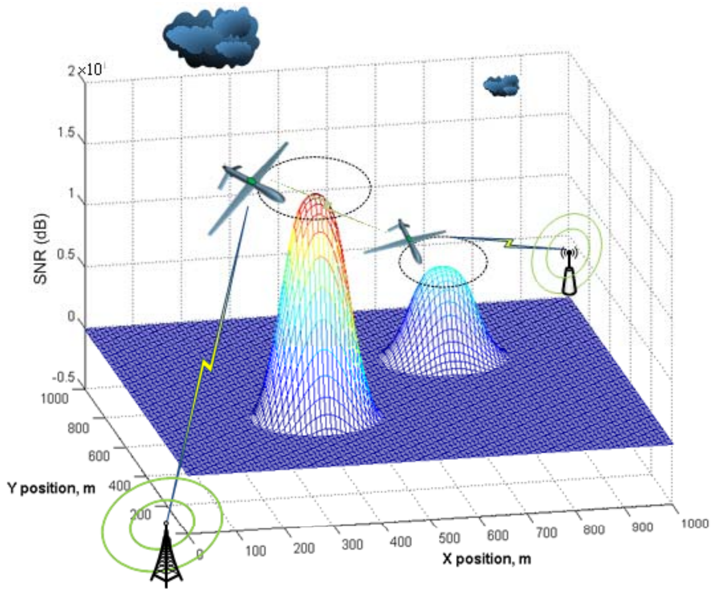


Concept for Sensor Networking Between Heterogeneous Vehicles

Strategy

❖Control Method

➢Methods for controlling flying platforms to operate continually at the maximum point of a performance function can be termed real-time optimization or extremum control



Approaches I

❖ Real-Time Optimization

- ➢ Cost Function : Communication performance
- ➢ Constraint : UAV positioning equation

$$\max_{\mathbf{x}_k \in D} J_k(\mathbf{x}_k) \quad \text{subject to } \mathbf{x}_{k+1} = f\left(\mathbf{x}_k, u_k\right)$$

- ❑ Cost Function (J)

$$J(\mathbf{x}_k) = J(x_k, y_k, z_k, \phi_k, \mathbf{x}_{node,i})$$

$\mathbf{x}_{node,i}$ = communications nodes (x_k, y_k, z_k, ϕ_k) = UAV position and attitude (bank)

- ❑ Equations of 3D/2D UAV Motion

$$f(\mathbf{x}_k): \begin{cases} x_{k+1} = x_k + v\cos\left(\psi_h\right)\Delta t \\ y_{k+1} = y_k + v\sin\left(\psi_h\right)\Delta t \end{cases}$$

where v is body-axis speed and ψ_h is the yaw angle of the vehicle

Approaches I

❖ Real-Time Optimization

- If partial derivatives of the cost function are known
- Solution: Extremum Control (Gauss-Newton Optimization)

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \mathbf{u}_k = \mathbf{x}_k - \alpha_k \mathbf{H}_k^{-1}(\mathbf{x}_k)\nabla J(\mathbf{x}_k)$$

where $\mathbf{H}_k = h_{ij}(\mathbf{x}_k) = \dfrac{\partial^2 J}{\partial x_{i,k}\partial x_{j,k}}(\mathbf{x}_k),\quad \nabla J(\mathbf{x}_k) = \left(\dfrac{\partial J}{\partial x_{1,k}}(\mathbf{x}_k),\ \cdots\ ,\dfrac{\partial J}{\partial x_{n,k}}(\mathbf{x}_k)\right)^T$

- Issue: 3-D Complex Optimization Problem

$$J(x_k, y_k, z_k, \phi_k, \mathbf{x}_{node,i}) = J(\phi_k, \|\mathbf{d}\|)$$

where $\|\mathbf{d}\| = \sqrt{(x_{uav} - x_{node})^2 + (y_{uav} - y_{node})^2 + (z_{uav} - z_{node})^2}$

Methodology

❖ Gradient-Type Extremum Control

- ➢ Measured SNR is discontinuous and slow (1 Hz)
- ➢ Subjective to noise and cluttered environment
- ➢ Affected by the orientation of a UAV (fast maneuver)

✓ Computation of gradient/hessian values is nontrivial

❖ Approaches and Solutions

➢ Mathematical Communications Modeling

- Provide continuous reference values at fast mode
- Predict a maximum operation point

➢ Model-Free Adaptive Extremum Control

- Gradient is obtained by numerical method without model
- Robust to noise and cluttered environment

Milestones

- ❖Motivations
- ❖**Communication Modeling**
- ❖Self-Tuning Extremum Control
- ❖Flight Test Results

SNR Model for Cost Function

❑ Why Signal-to-Noise Ratio Model

$$C = W \log_2 (1 + SNR)$$ **: Shannon-Hartley Theorem**

where C is channel capacity (bits per second) W - bandwidth (Hz) of the channel

✓**Channel capacity (*C*) is proportional to the SNR and the bandwidth (*W*)**

❑ Signal-to-Noise Ratio (SNR) Model

$$\mathrm{SNR}(dBm) = \frac{P_r(dBm)}{P_n(dBm)} = \left(\frac{\lambda}{4\pi \|\mathbf{d}\|}\right)^2 \frac{G_t G_r}{L_{ap}}$$

where $P_r(dBm)$ is the receiver power $P_n(dB)$ is noise power (-95 dBm)

$G_r(dB)$ is receiver antenna gain $G_t(dB)$ is transmitter antenna gain

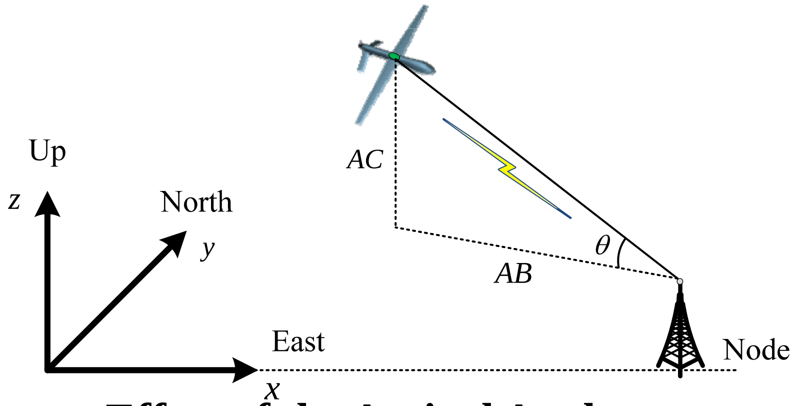
$\lambda = c/f$ where f is the transmission frequency $c = 3 \times 10^8$ m/s $\|\mathbf{d}\|$ = distance

$L_p(dB) \equiv (4\pi \|\mathbf{d}\| / \lambda)^2$ is path loss

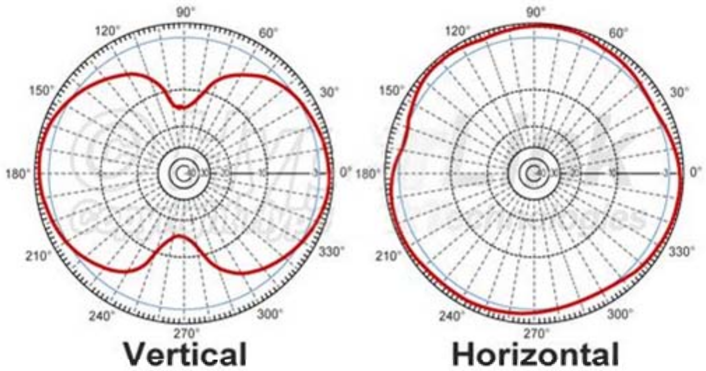
$L_{ap}(dB)$ is antenna pattern loss

Antenna Pattern Loss on SNR

❑ Model for UAV Orientation Effects



Effect of the Arrival Angle on Antenna Pattern Loss



Antenna Pattern Loss in the Horizontal and Vertical Planes

➢ **Antenna Pattern Loss : Function of Arrival Angle** $\gamma_i(t)$

$$\gamma_i(t) = -\theta_i(t) - \phi(t)\sin\left(\varphi_i(t) - \psi(t)\right)$$

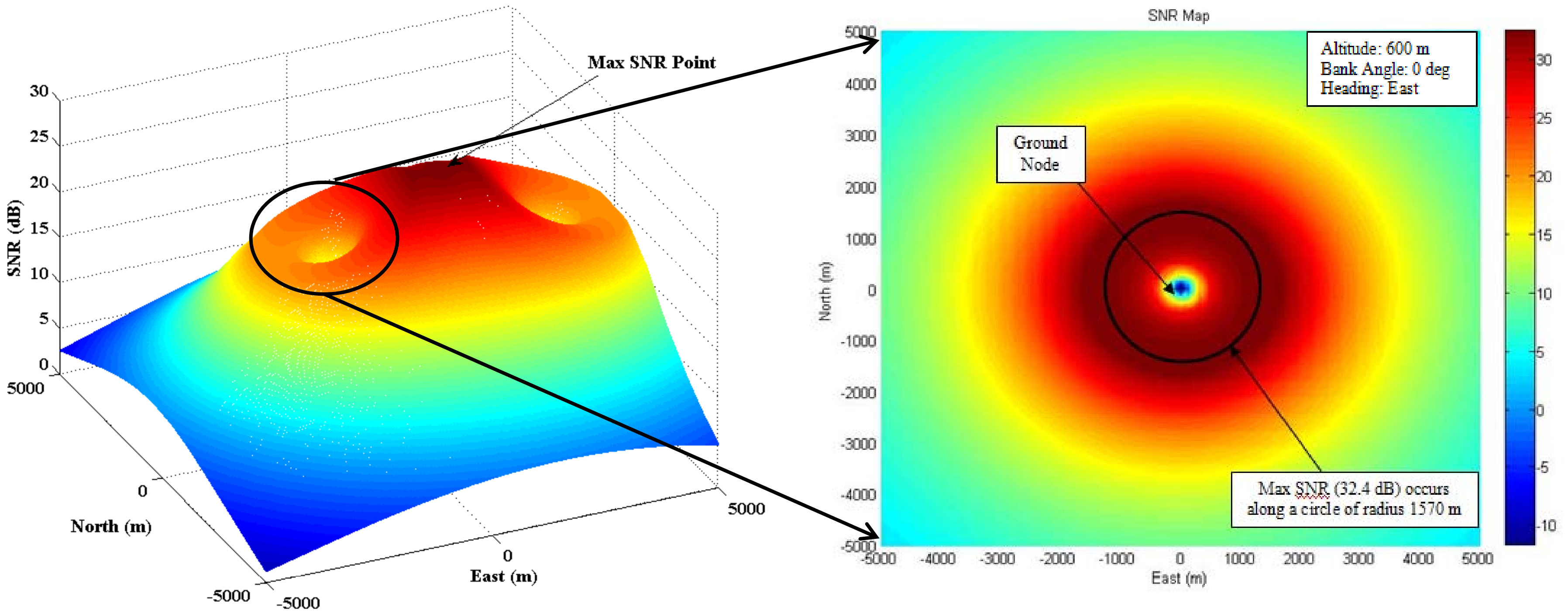
which is the angle between the incident ray and horizontal wing of a UAV

$$\theta_i(t) = \tan^{-1}\left(\frac{\left(z(t) - z_{node,i}\right)}{\sqrt{\left(x(t) - x_{node,i}\right)^2 + \left(y(t) - y_{node,i}\right)^2}}\right) \qquad \varphi_i(t) = \tan^{-1}\left(\frac{y(t) - y_{node,i}}{x(t) - x_{node,i}}\right)$$

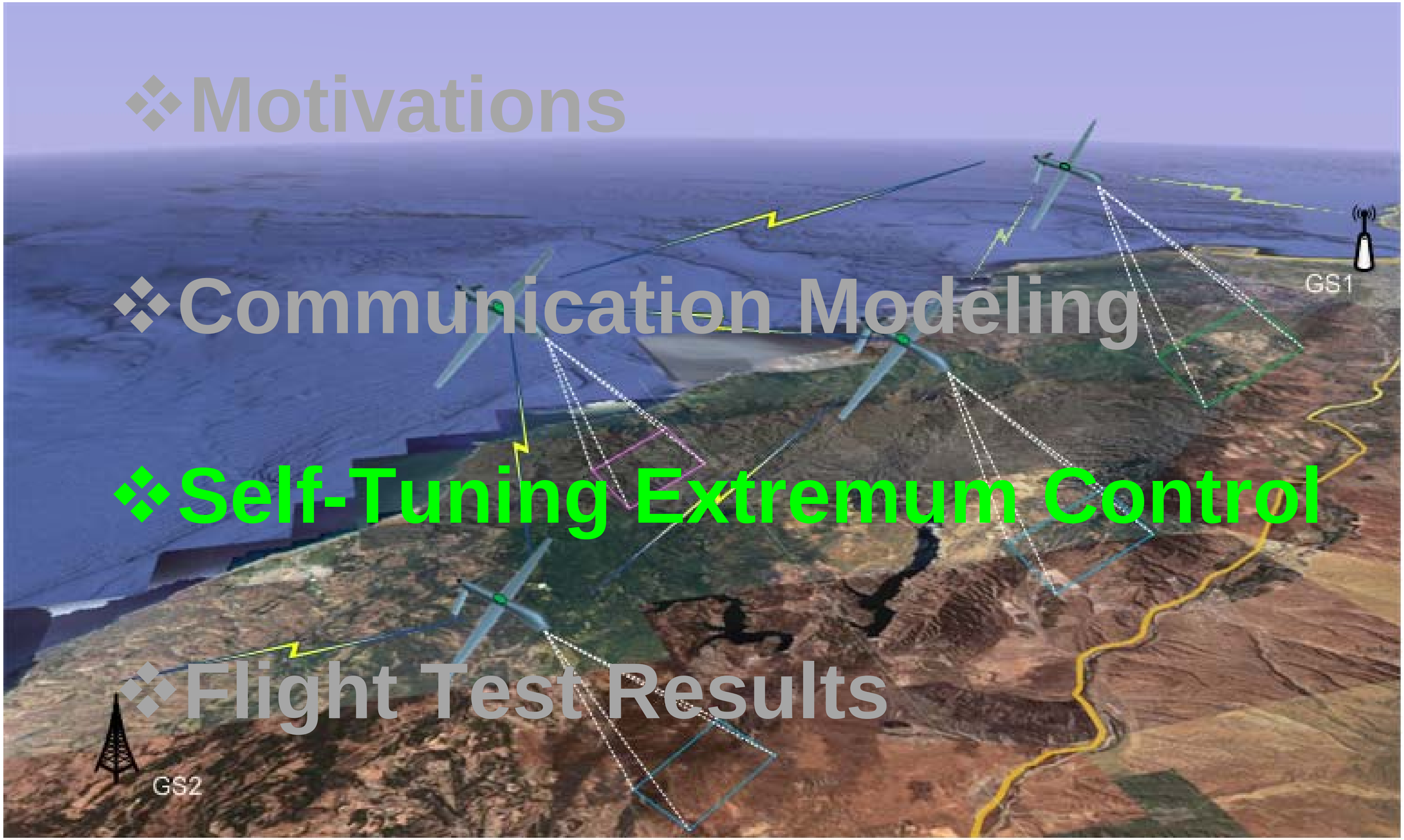
$\phi(t)$ is the UAV bank angle $\quad$ $\psi(t)$ is the heading angle of the UAV $\quad$ $\varphi_i(t)$ is the bearing angle

SNR Map Example

- Static SNR Map in East-North-Up coordinates
  - Fixed altitude, heading & bank angle
  - Path loss, Antenna pattern loss



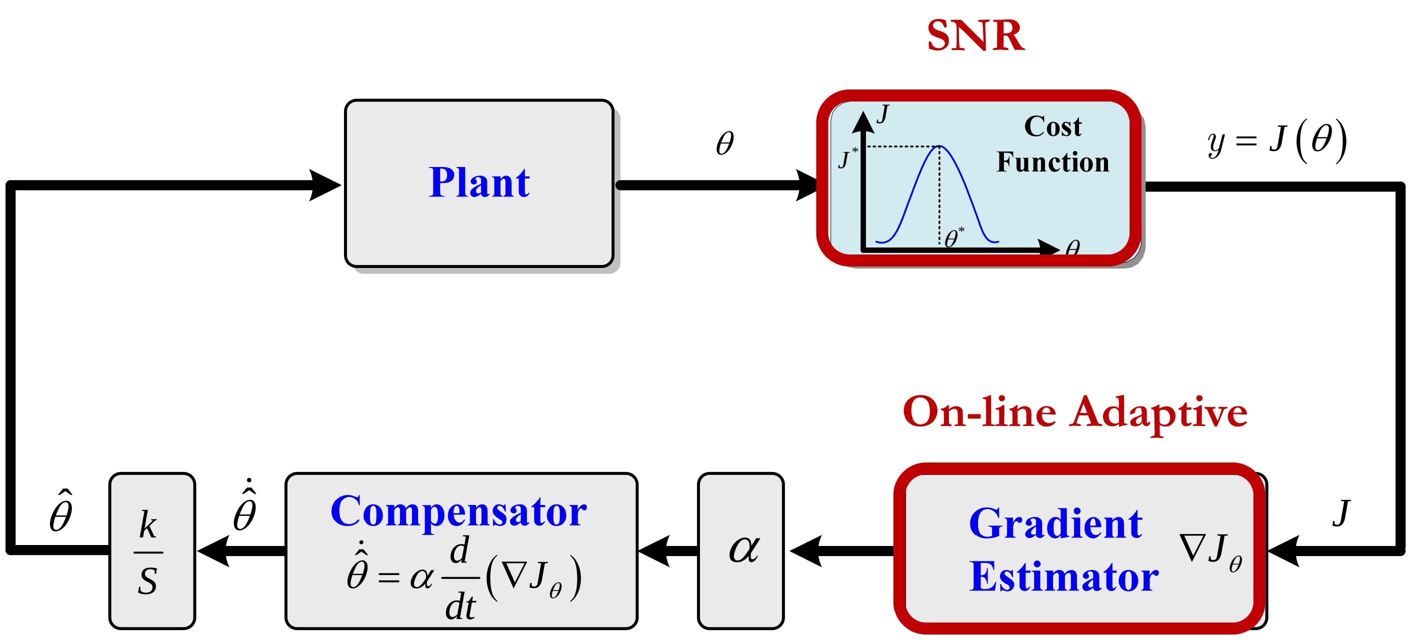
SNR Map (3-D View) **SNR Map (2-D Top View)**



- ❖Motivations
- ❖Communication Modeling
- ❖**Self-Tuning Extremum Control**
- ❖Flight Test Results

Self-Tuning Extremum Control

- Use on-line gradient estimation of SNR function to drive the set point to its max location
- On-line estimator does not require a precise model

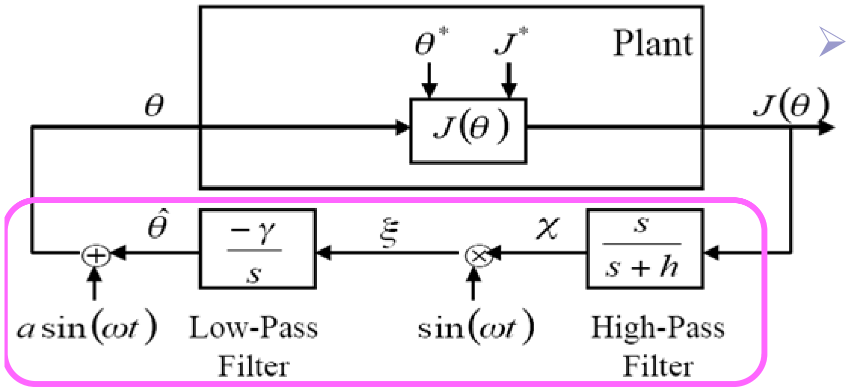


Self-Estimating Extremum Control Architecture

On-Line Gradient Estimator

❑ Perturbation Based Gradient Estimator

- The purpose is to make θ-θ^* as small as possible, so that the output is driven to its minimum J^*



$$J(\theta) = J^* + \frac{J''}{2}(\theta - \theta^*)^2, \quad J'' > 0$$

Peak-Seeking Architecture
(Stability Proof by Kristic, 2001)

- How It Works ?
  - Let $y = J(\theta)$ be a general mapping function
  - Assume $\hat{\theta}$ be a current parameter
  - Perturbation $a\sin wt$ around $\hat{\theta}$ leads to

$$y = J\left(\hat{\theta} + a\sin wt\right) \approx J\left(\hat{\theta}\right) + a\left.\frac{\partial J}{\partial \theta}\right|_{\theta=\hat{\theta}} \sin wt$$

- Applying high-pass filter (differentiator) gets rid of constant term and leads to

$$y_H \approx a\left.\frac{\partial J}{\partial \theta}\right|_{\theta=\hat{\theta}} \sin wt$$

On-Line Gradient Estimator

- Demodulating y_H with $\sin wt$ divides the signal into a low-frequency signal and high-frequency signal

$$\varsigma = \frac{1}{2} a \left.\frac{\partial J}{\partial \theta}\right|_{\theta=\hat{\theta}} - \frac{1}{2} a \left.\frac{\partial J}{\partial \theta}\right|_{\theta=\hat{\theta}} \cos 2wt$$

- Applying low-pass filter (integrator) gets rid of the sinusoidal term and provides an estimate of the gradient of $J(\theta)$

$$y_L \approx \frac{1}{2} a \left.\frac{\partial J}{\partial \theta}\right|_{\theta=\hat{\theta}}$$

- The estimated gradient can be expressed by the parameter change

$$\dot{\hat{\theta}} = k \frac{1}{2} a \left.\frac{\partial J}{\partial \theta}\right|_{\theta=\hat{\theta}}$$

Self-Tuning Estimator

- Denote $\tilde{\theta} = \hat{\theta} - \theta^*$ the convergence error, and taking a derivative of the errors leads to

$$\dot{\tilde{\theta}} = \dot{\hat{\theta}} \approx k \frac{1}{2} a J''\left(\theta^*\right)\tilde{\theta}$$

- which become stable with a proper choice of the parameter, *a* and *k* i.e., $kaJ''\left(\theta^*\right) < 0$

❑ How Self-Tuning Extremum Control Works ?

- Key idea is to integrate an on-line gradient estimator into an extremum control to get optimal location for UAVs

❑ Consider 2-D Motion in $\{I\}$ Frame

$$f(\mathbf{x}_k):\begin{cases}\dot{x}(t)=v(t)\cos\left(\psi_h(t)\right)\\ \dot{y}(t)=v(t)\sin\left(\psi_h(t)\right)\end{cases}$$

where v is body-axis speed and ψ_h is the yaw angle of the vehicle

❑ Motion with Constant Speed

$$x(t)=v\cos\left(\psi_h(t)\right)=f_1(\psi_h(t),x_0)$$
$$y(t)=v\sin\left(\psi_h(t)\right)=f_2(\psi_h(t),y_0)$$

where $v=const$

Autonomous Controller Design

- Then SNR function becomes an implicit function of heading angle

$$J = SNR\big(x(t), y(t)\big) = SNR\big(x(\psi_h(t)), y(\psi_h(t))\big) = J\big(\psi_h(t)\big)$$

- Gradient Descent Extremum Control is expressed by

$$\psi_{k+1} = \psi_k + \alpha_k \nabla J_\psi$$

where $\nabla J_\psi = \partial J / \partial \psi \in \Re$

- Assume that SNR is a quadratic function

$$J\big(\hat{\psi}(t)\big) = J^* + \frac{\mu}{2}\big(\hat{\psi}(t) - \psi^*\big)^2 + w(t)$$

$\hat{\psi}(t)$ is the current heading angle estimate

J^* is the maximum attainable value of the cost function, $w(t)$ is a zero-mean white noise

μ is the sensitivity of the quadratic curve **Unknown**

ψ^* is the heading angle maximizing J

➢ Adaptive Convergence Rate α_k

- Armijo-Wolfe Conditions

$$J(\mathbf{x}_k + \alpha_k \mathbf{d}_k) \le J(\mathbf{x}_k) + c_1 \alpha_k \mathbf{d}_k^T \nabla J(\mathbf{x}_k)$$

$$\mathbf{d}_k^T \nabla J(\mathbf{x}_k + \alpha_k \mathbf{d}_k) \ge c_2 \mathbf{d}_k^T \nabla J(\mathbf{x}_k)$$

where $0 < c_1 < c_2 < 1$

the *Armijo* condition that prevents steps that are too long

the *Wolfe* condition which restricts steps that are too short

- Adaptive Convergence Control Law

$$\alpha_{k+1} = \gamma\, \alpha_k \text{, where } \begin{cases} 0 < \gamma < 1, & \text{if } \Delta J_{k+1} > \tau_{tv} \\ \gamma \ge 1, & \text{else } \Delta J_{k+1} < \tau_{tv} \end{cases}$$

where

$\Delta J_{k+1} = J_{k+1} - J_k$ or $d(\nabla J_{\hat{\psi}(t)})/dt$

τ_{tv} : a specified threshold value

$$u_{com}(t) = \begin{cases} \dot{\psi}_{com}(t) = \dot{\psi}_{ss} & \text{if } \left|\dot{\psi}_{com}(t) - \dot{\psi}_{ss} = v/R_{ss}\right| \le \varepsilon_{ss} \\ \dot{\psi}_{com}(t) = \dot{\psi}_{ss} + \mu\, \gamma\, \alpha(t)\, \dot{\hat{\psi}}(t) & \text{other} \end{cases}$$

- Applying On-Line Gradient Estimator

$$\nabla J_{\hat{\psi}(t)} \equiv \frac{\partial J\left(\hat{\psi}(t)\right)}{\partial \hat{\psi}(t)} = \mu\left(\hat{\psi}(t) - \psi^{*}\right), \qquad \frac{d}{dt}\left(\nabla J_{\hat{\psi}(t)}\right) = \mu\left(\dot{\hat{\psi}}(t)\right)$$

- Then the extremum controller is expressed by

$$\dot{\psi}_{com}(t) = \frac{d\psi(t)}{dt} = \alpha(t)\frac{d}{dt}\left(\nabla J_{\psi}\right) = \mu\alpha(t)\dot{\hat{\psi}}(t)$$

On-line Gradient Estimator

$\alpha(t)$: step length along the direction ∇J — Optimal value can be obtained by *Armijo-Wolfe* conditions

- Orbit Circle Guidance at Final Steady-Stage

$$u(t) = \begin{cases} \dot{\psi}_{com}(t) = \dot{\psi}_{ss} & if \ \left|\dot{\psi}_{com}(t) - \dot{\psi}_{ss} = v / R_{ss}\right| \le \varepsilon_{ss} \\ \dot{\psi}_{com}(t) = \dot{\psi}_{ss} + \mu\alpha(t)\dot{\hat{\psi}}(t) & other \end{cases}$$

$\dot{\psi}_{ss}$ is introduced to guarantee that the UAV will orbit with a constant radius R_{ss} at the final stage.

$R_{ss} = v / \dot{\psi}_{ss}$: a final approach circle radius.

Milestones

- Motivations
- Communication Modeling
- Self-Tuning Extremum Control
- **Flight Test Results**

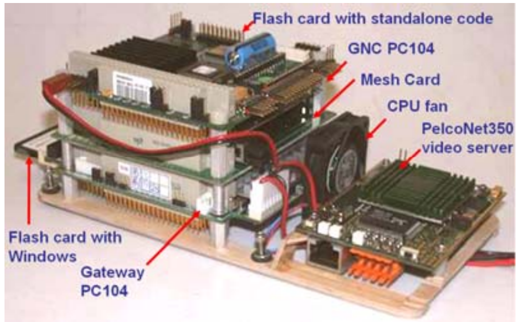
Flight Test Systems

Rascal 110 UAV (ARF Airframe)

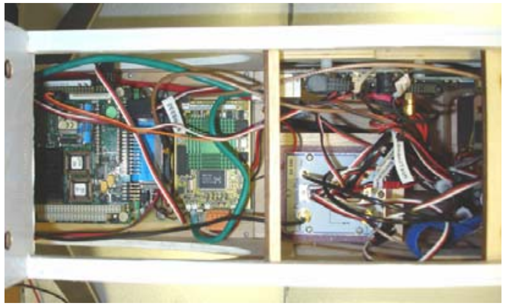
Piccolo Plus Autopilots

2-Stroke Gas Engine

Engine Mount



Onboard PC104 & Payload Stack

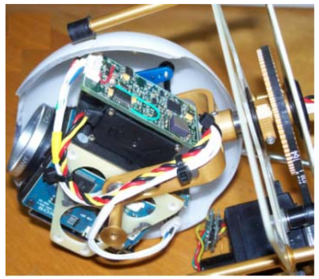


Avionics bay of Rascal UAV

Mobile GCS

- ❖ **Rapid Flight Test Design Keys**
- ❑ Reduce development time
- ❑ Upgrade is flexible
- ❑ Convenience of high level programming

Tracking antenna and Wave Relay mesh link

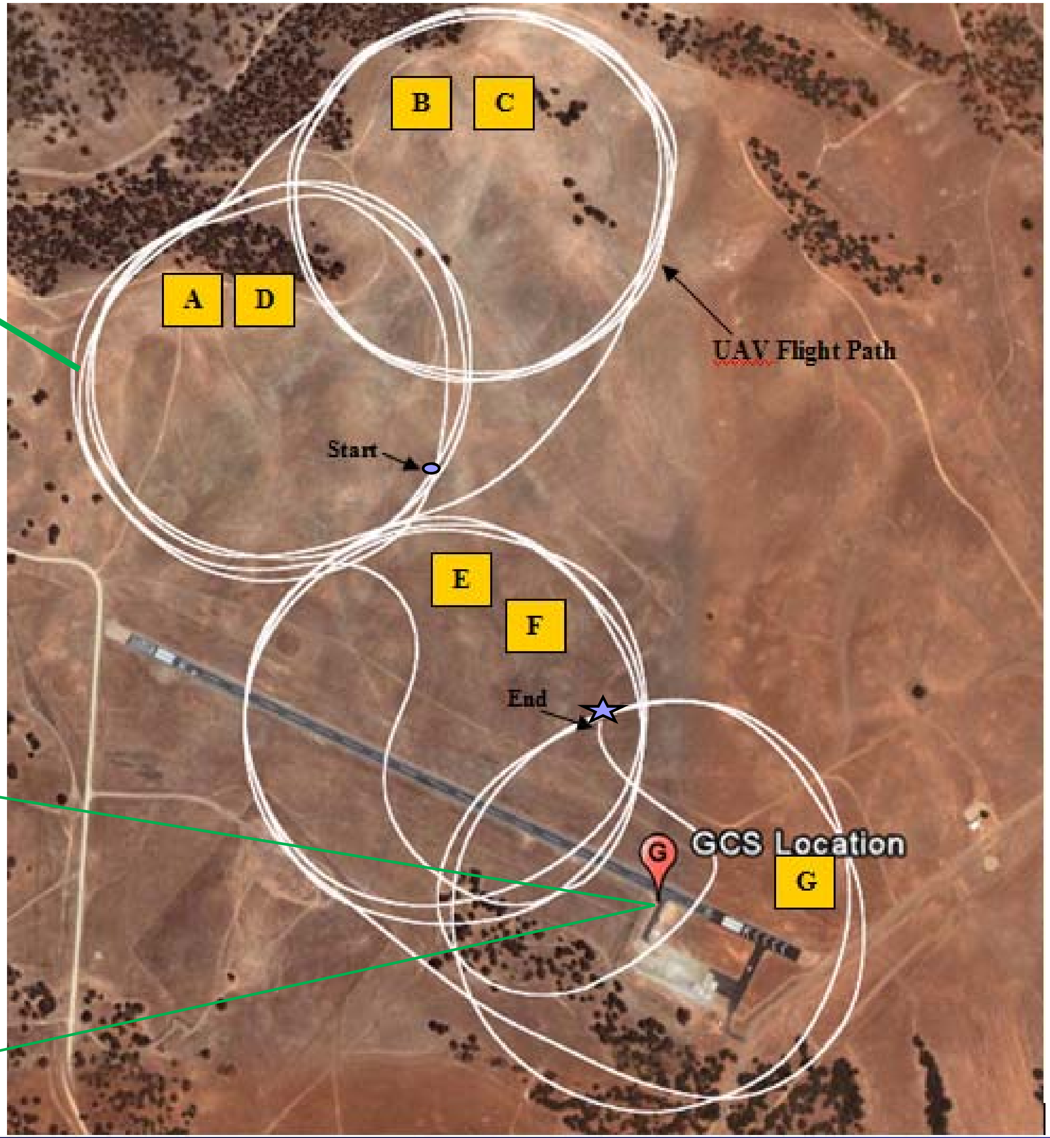


Gimbal Camera

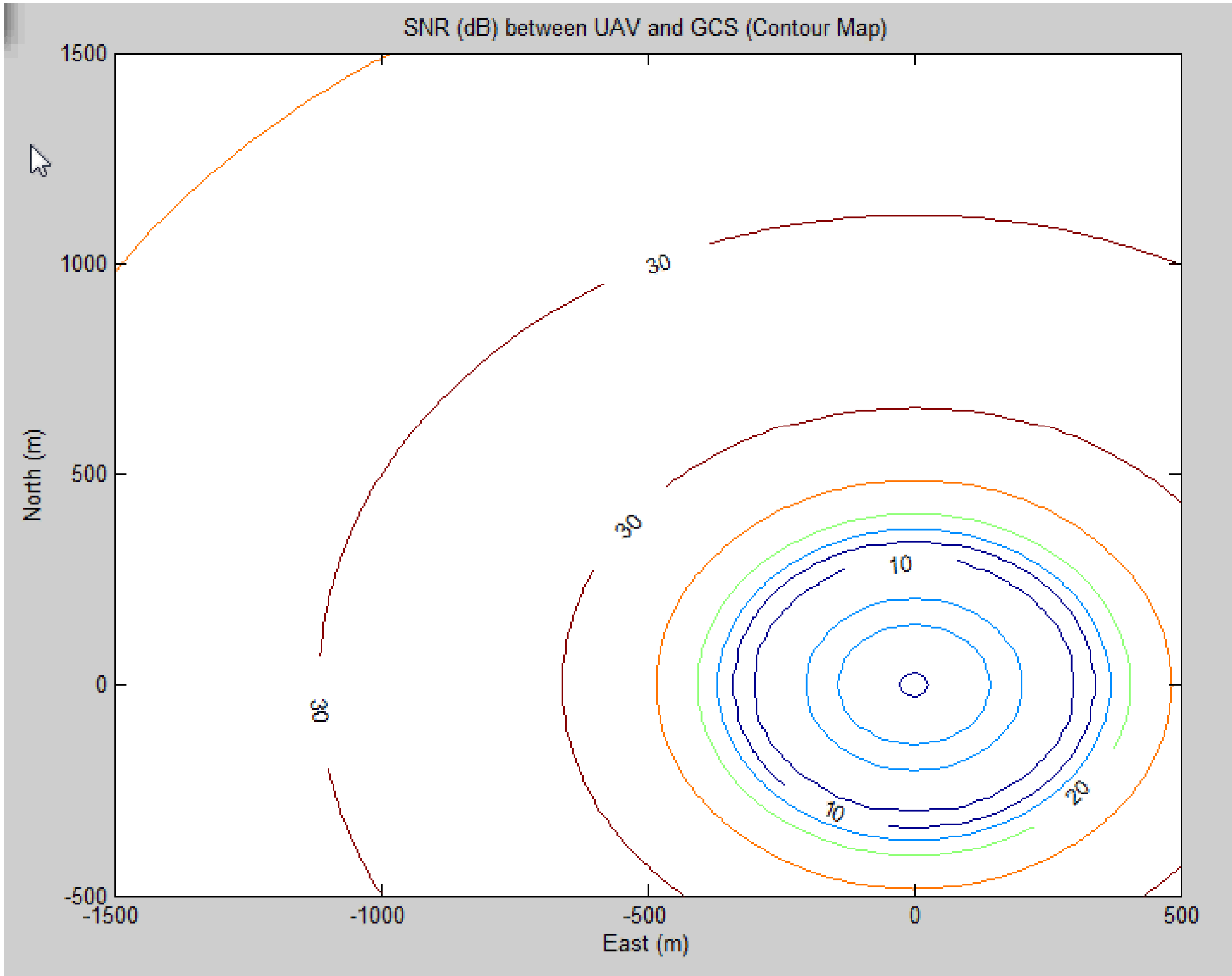
Model Verification Flight Test

3 dB Omni-Directional Antenna

9 dB Sector Antenna



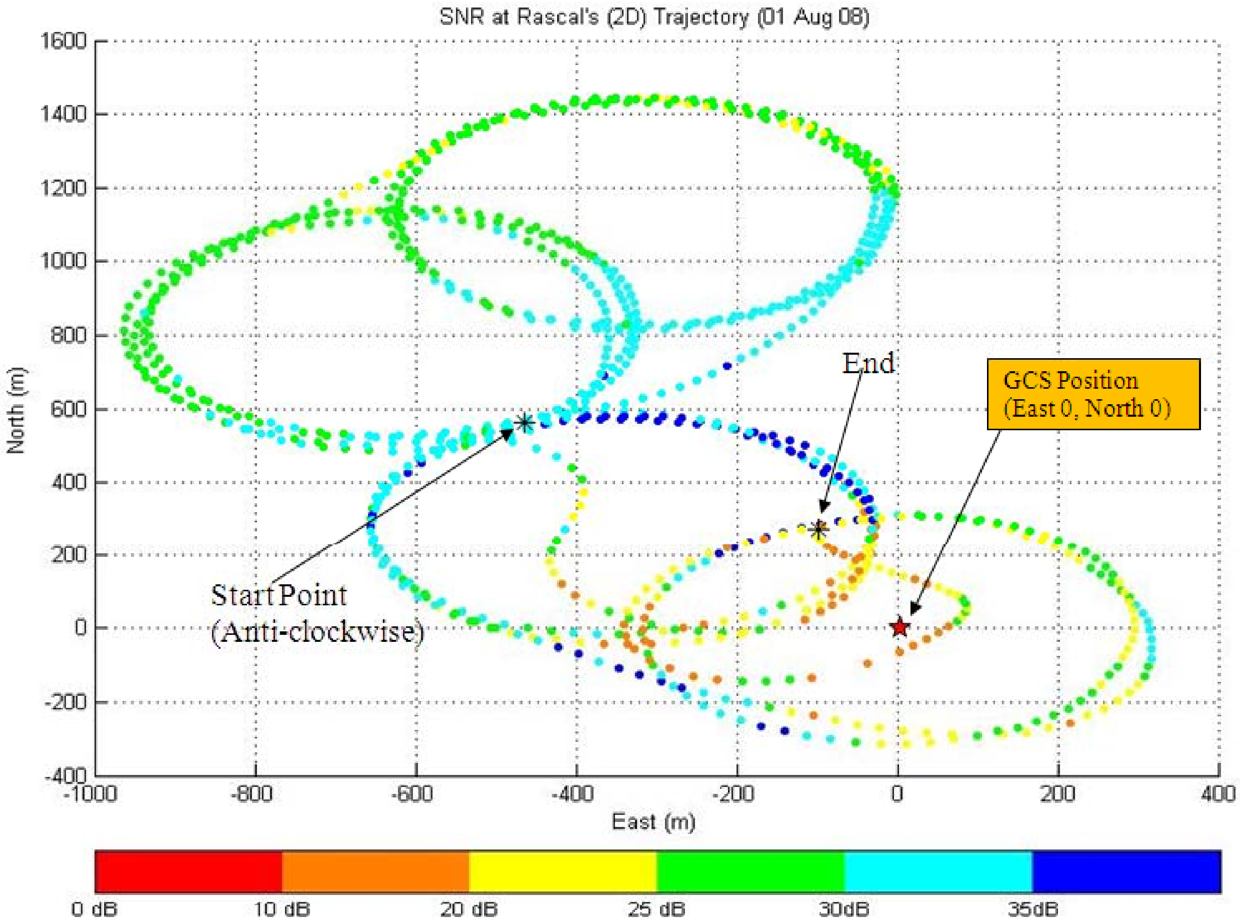
SNR Model Verification



Movie

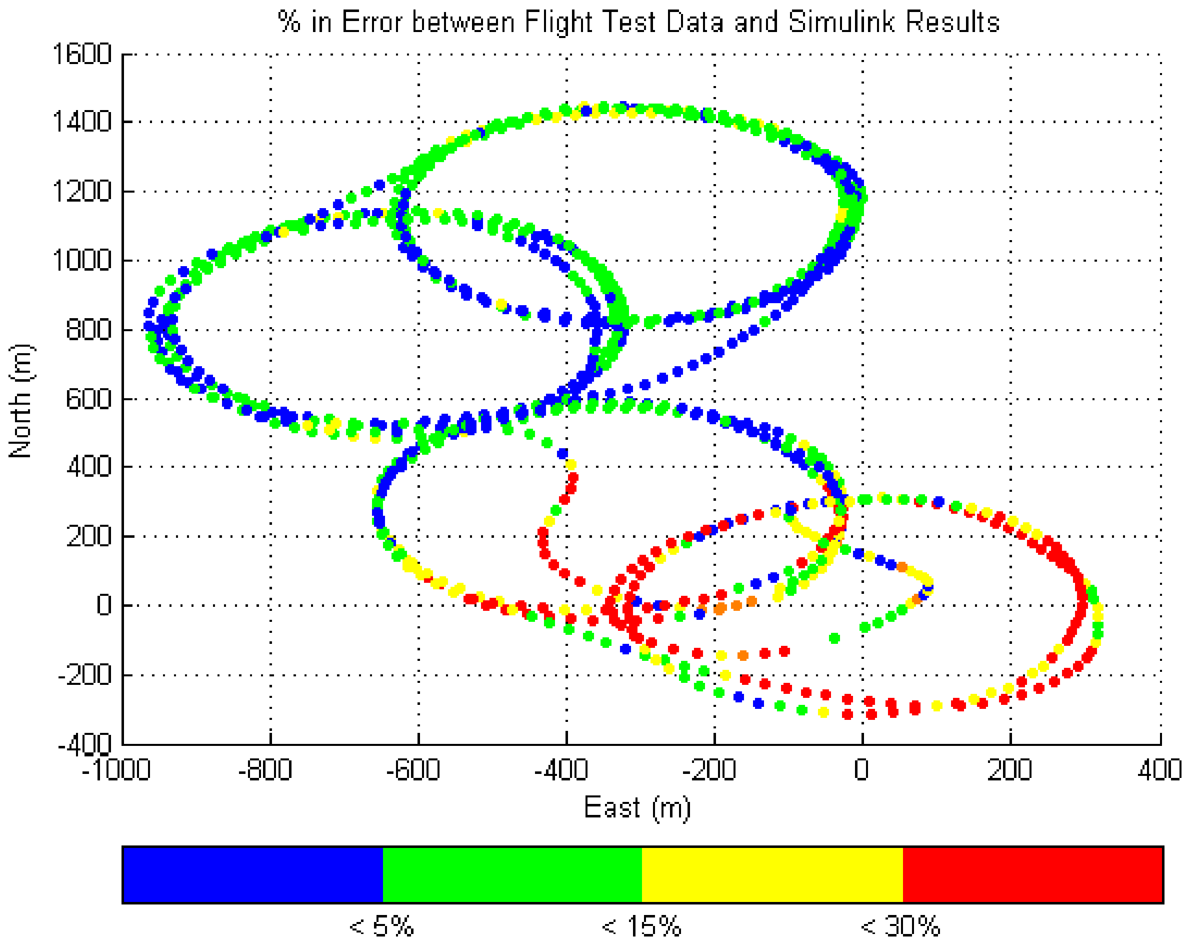
SNR Model Verification with respect to UAV Trajectories

SNR Model Verification



SNR Variation with respect to UAV Trajectories

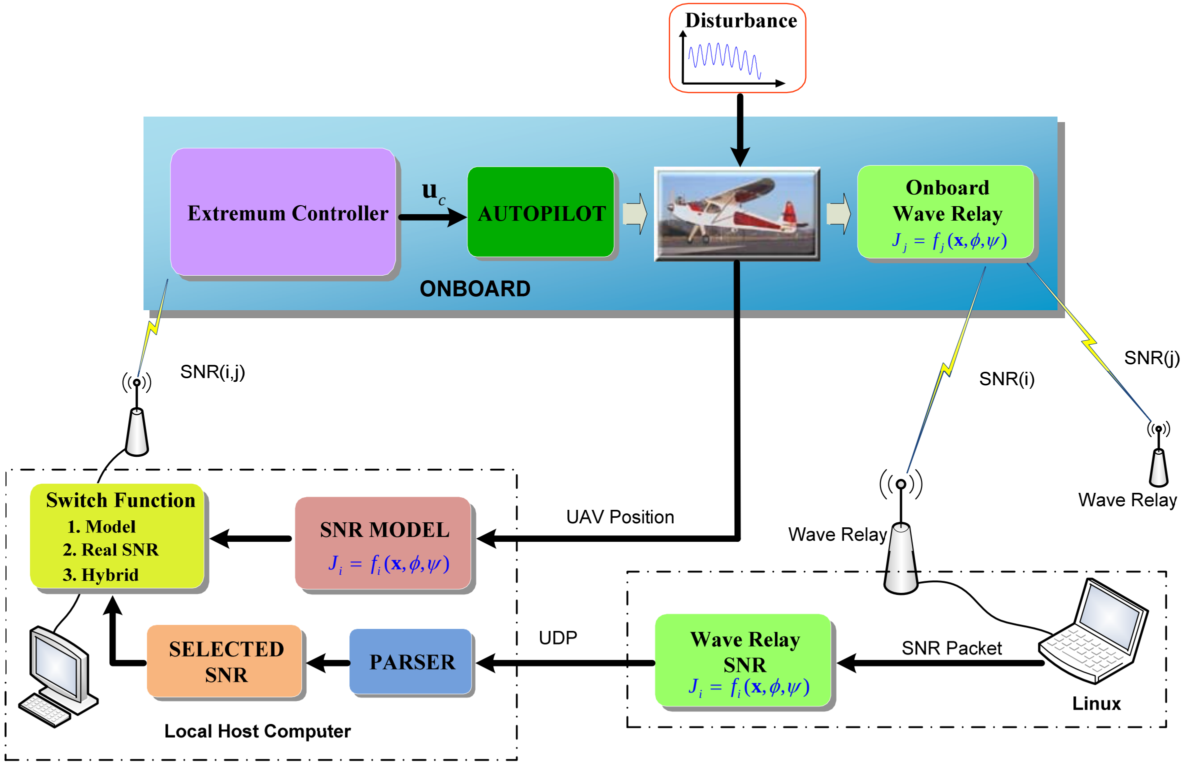
Comparison with SNR Model



SNR Error Plots Between Real and Model Values

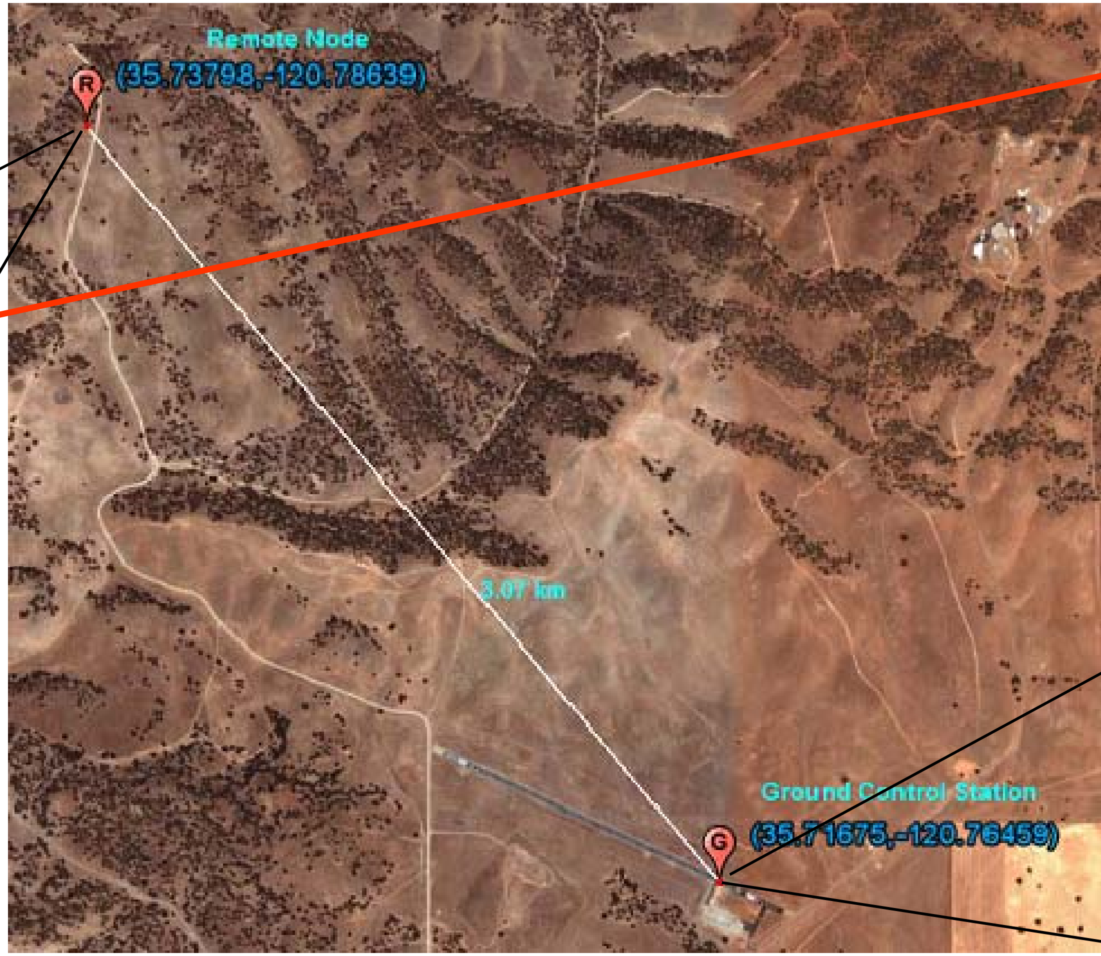
High Band Comms Flight Test

- Flight Test (Nov. 20, 2008)
  - Validate the designed onboard adaptive self-tuning controller & the communication models



Network Coverage Control using Extremum-Seeking Control

Flight Test Set-Up



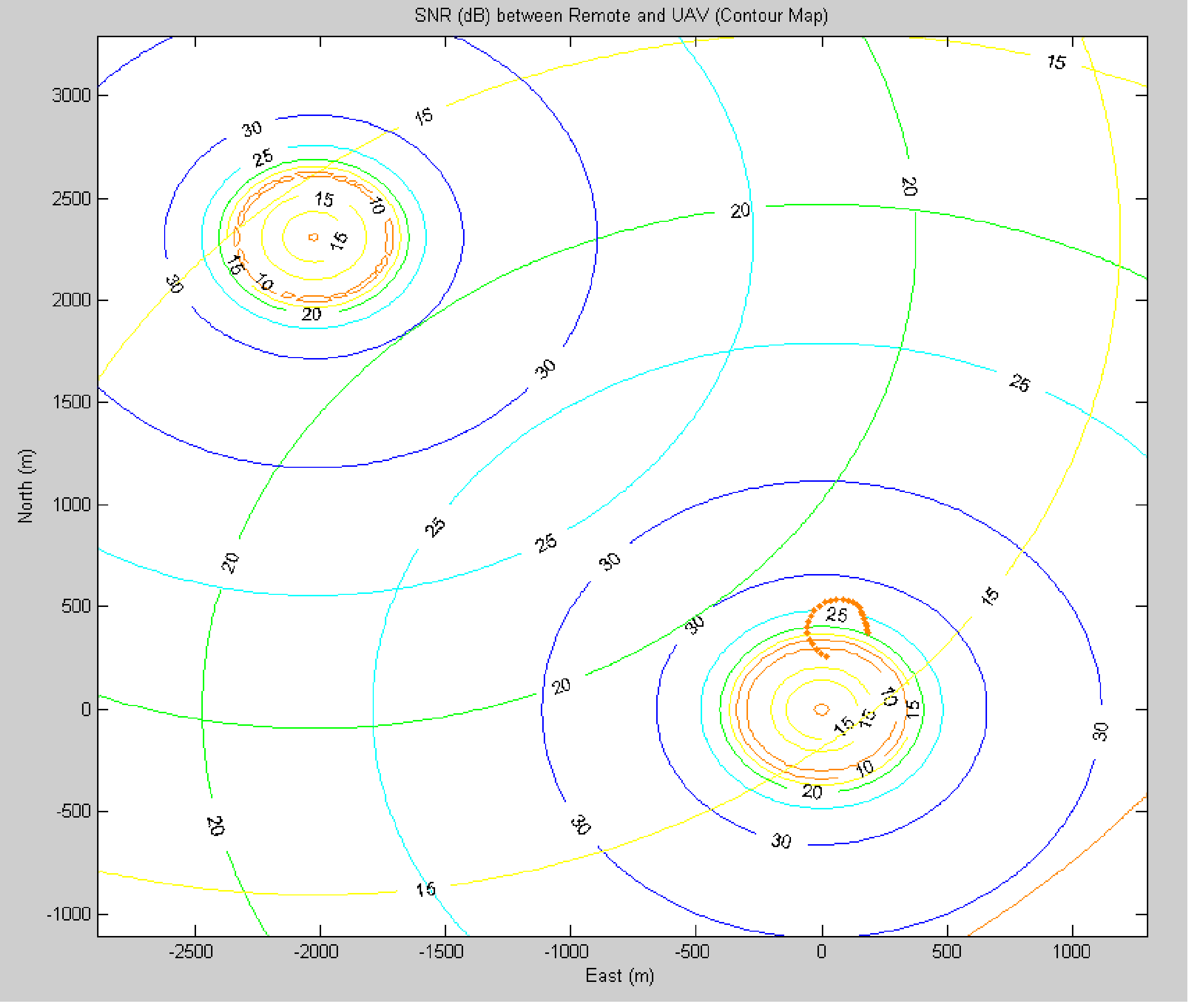
Remote Node

GCS

Sensor Node Locations & Flight Setup in Camp Roberts

UAV Trajectory over SNR MAP

(Movie)



UAV Trajectory Control for Max Communication Links (SNR)

UAV Path over SNR Map

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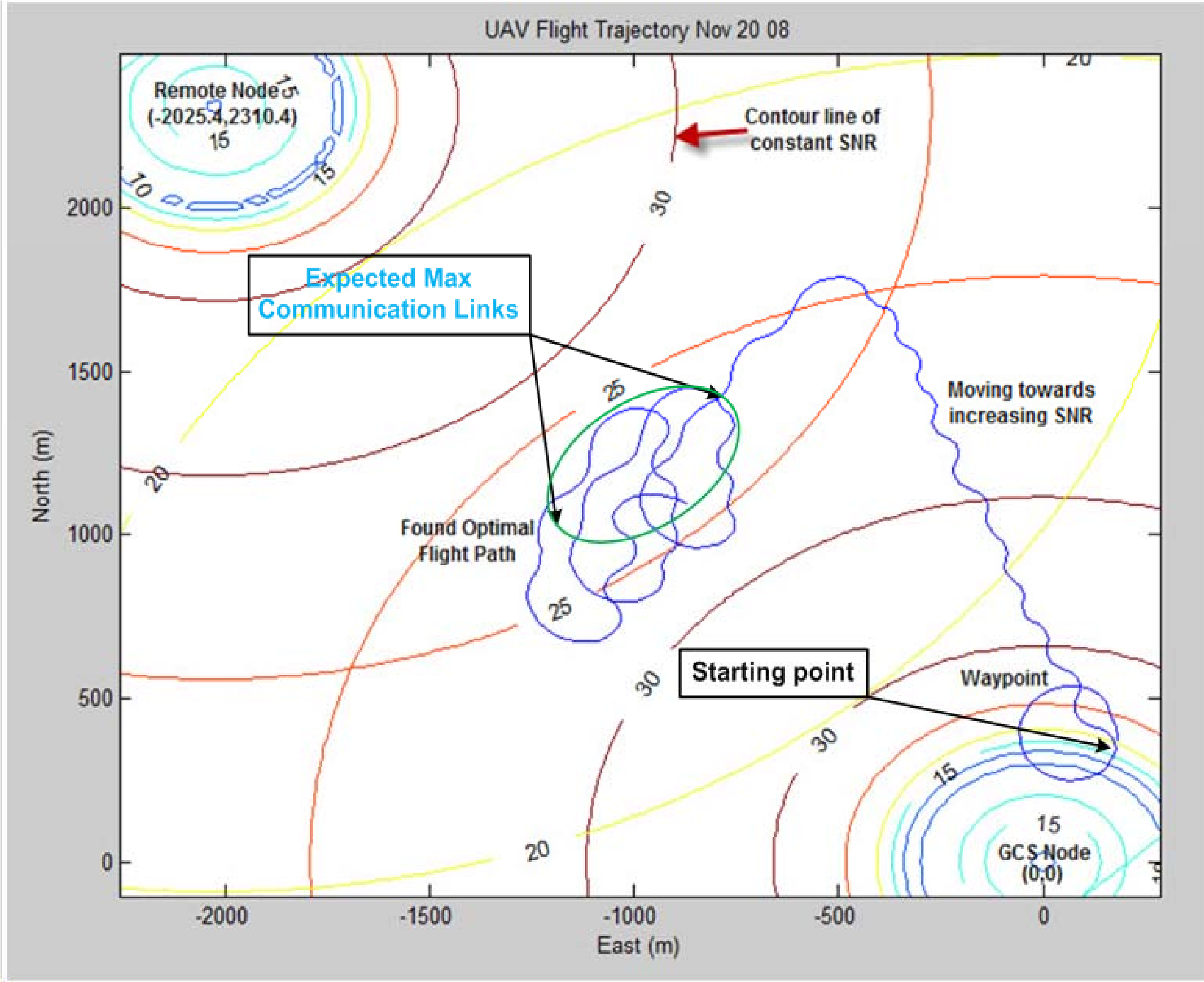
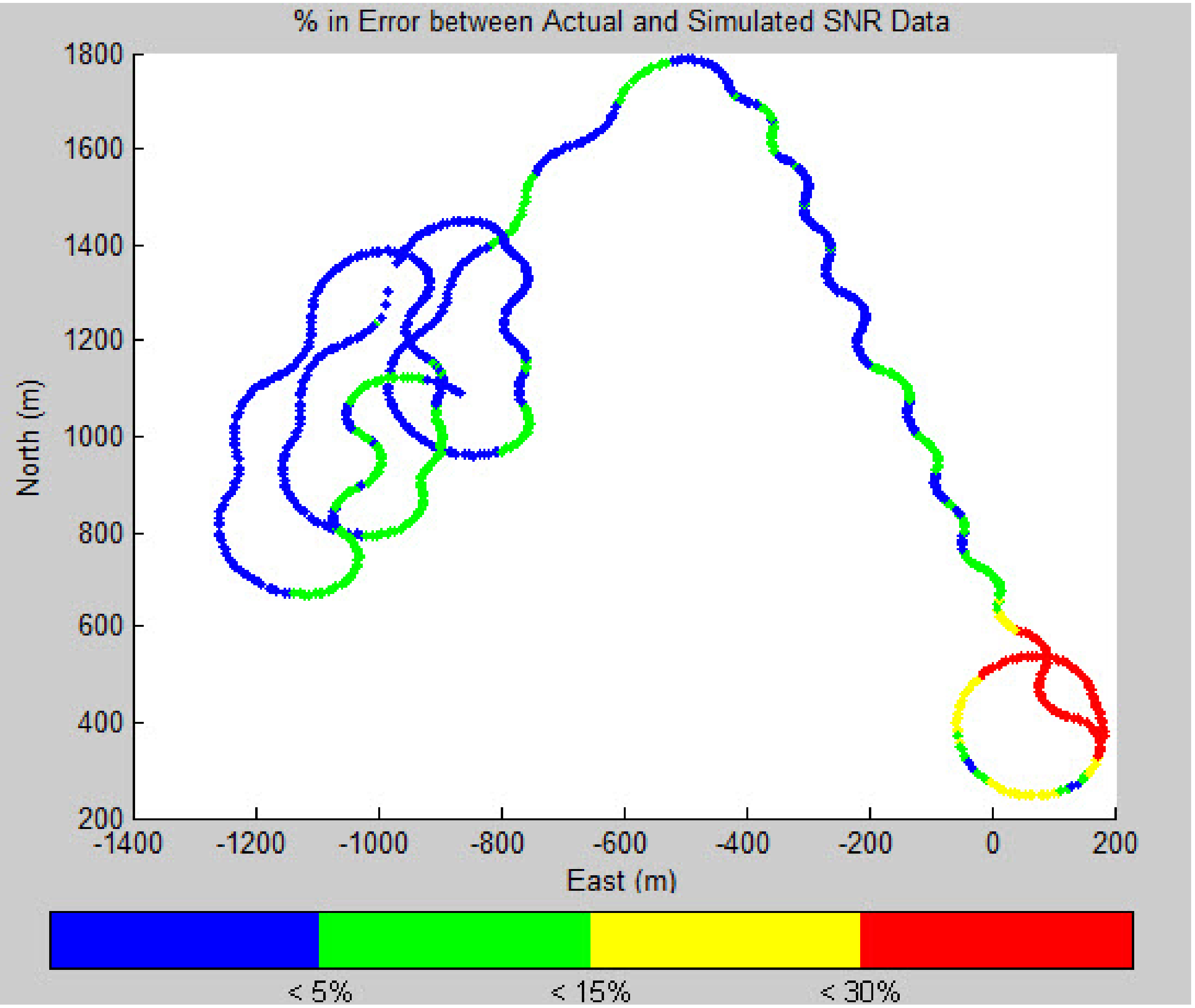


Plot of UAV Trajectory over SNR Maps

SNR Model Errors



Plot of SNR Errors Between Model and Observation Ones

Conclusions

- Communication Propagation Model
  - Communication propagation model was developed, which include the effects of the path loss, antenna pattern loss, and the orientation of aerial platforms
  - Proposed models were validated through real flight tests
- Self-Tuning Extremum Control for UAVs Location
  - On-lie adaptive gradient estimator was integrated into an extremum control architecture
  - Proposed self-estimating extremum control is robust to even low signal-to-noise ratio signal
  - Effectiveness of the self-tuning optimizer was validated through real time flight tests
- Applicable for Decentralized Network Coverage Control