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
Sensor Networks with Multiple UAS

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 Issues

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

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

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

$$\max_{x_k \in D} J_k(x_k) \quad \text{subject to} \quad x_{k+1} = f(x_k, u_k)$$

Cost Function (J)

$$J(x_k) = J(x_k, y_k, z_k, \phi_k, x_{node,i})$$

$x_{node,i} = \text{communications nodes } (x_k, y_k, z_k, \phi_k) = \text{UAV position and attitude (bank)}$

Equations of 3D/2D UAV Motion

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

where $v$ is body-axis speed and $\psi_h$ is the yaw angle of the vehicle
Real-Time Optimization

- If partial derivatives of the cost function are known

Solution: Extremum Control (Gauss-Newton Optimization)

\[ x_{k+1} = x_k + u_k = x_k - \alpha_k H_k^{-1}(x_k) \nabla J(x_k) \]

where \( H_k = h_{ij}(x_k) = \frac{\partial^2 J}{\partial x_{i,k} \partial x_{j,k}}(x_k), \quad \nabla J(x_k) = \left( \frac{\partial J}{\partial x_{1,k}}(x_k), \ldots, \frac{\partial J}{\partial x_{n,k}}(x_k) \right)^T \)

Issue: 3-D Complex Optimization Problem

\[ J(x_k, y_k, z_k, \phi_k, x_{node,i}) = J(\phi_k, \|d\|) \]

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

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

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 \( \|d\| = \) distance

\[
L_p(dB) \equiv (4\pi \|d\| / \lambda)^2 \text{ is path loss}
\]

\[
L_{\varphi}(dB) \text{ is antenna pattern loss}
\]
Model for UAV Orientation Effects

Effect of the Arrival Angle on Antenna Pattern Loss


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

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

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

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

$$\varphi_i(t) = \tan^{-1}\left(\frac{y(t) - y_{node,i}}{x(t) - x_{node,i}}\right)$$

$\phi(t)$ is the UAV bank angle $\psi(t)$ is the heading angle of the UAV $\varphi_i(t)$ is the bearing angle
- Static SNR Map in East-North-Up coordinates
  - Fixed altitude, heading & bank angle
  - Path loss, Antenna pattern loss
Milestones

❖ Motivations

❖ Communication Modeling

❖ Self-Tuning Extremum Control

❖ Flight Test Results
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.
Perturbation Based Gradient Estimator

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

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

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

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

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

$$y_H \approx a \frac{\partial J}{\partial \theta}_{\theta=\hat{\theta}} \sin wt$$
• Demodulating $y_H$ with $\sin \omega t$ divides the signal into a low-frequency signal and high-frequency signal

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

• 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

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

Self-Tuning Estimator

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

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

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

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

where $v$ is body-axis speed and $\psi_h$ is the yaw angle of the vehicle.

Motion with Constant Speed

$$x(t) = v \cos(\psi_h(t)) = f_1(\psi_h(t), x_0)$$

$$y(t) = v \sin(\psi_h(t)) = f_2(\psi_h(t), y_0)$$

where $v = \text{const}$
Then SNR function becomes an implicit function of heading angle:

\[
J = SNR(x(t), y(t)) = SNR(x(\psi_h(t)), y(\psi_h(t))) = J(\psi_h(t))
\]

Gradient Descent Extremum Control is expressed by:

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

where \( \nabla J_{\psi} = \frac{\partial J}{\partial \psi} \in \mathbb{R} \)

Assume that SNR is a quadratic function:

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

\( \hat{\psi}(t) \) is the current heading angle estimate,
\( J^* \) is the maximum attainable value of the cost function,
\( w(t) \) is a zero-mean white noise,
\( \mu \) is the sensitivity of the quadratic curve,
\( \psi^* \) is the heading angle maximizing \( J \).
Adaptive Convergence Control

Adaptive Convergence Rate  \( \alpha_k \)

- Armijo-Wolfe Conditions

\[
J(x_k + \alpha_k d_k) \leq J(x_k) + c_1 \alpha_k d_k^T \nabla J(x_k)
\]

\[
d_k^T \nabla J(x_k + \alpha_k d_k) \geq c_2 d_k^T \nabla J(x_k)
\]

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

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

where

\[
\Delta J_{k+1} = J_{k+1} - J_k \text{ or } d(\nabla J(\psi(t)))/dt
\]

\( \tau_{tv} : \) a specified threshold value

\[
u_{com}(t) = \begin{cases} 
\dot{\psi}_{com}(t) = \dot{\psi}_{ss} & \text{if } |\dot{\psi}_{com}(t) - \dot{\psi}_{ss}| = v / R_{ss} \leq \varepsilon_{ss} \\
\dot{\psi}_{com}(t) = \dot{\psi}_{ss} + \mu \gamma \alpha(t) \dot{\psi}(t) & \text{other}
\end{cases}
\]
Applying On-Line Gradient Estimator

\[
\nabla J_{\dot{\psi}(t)} = \frac{\partial J(\dot{\psi}(t))}{\partial \dot{\psi}(t)} = \mu (\dot{\psi}(t) - \psi^*) , \quad \frac{d}{dt}(\nabla J_{\dot{\psi}(t)}) = \mu (\dot{\psi}(t))
\]

Then the extremum controller is expressed by

\[
\dot{\psi}_{com}(t) = \frac{d\psi(t)}{dt} = \alpha(t) \frac{d}{dt}(\nabla J_{\dot{\psi}}) = \mu \alpha(t) \dot{\psi}(t)
\]

\[\alpha(t) : \text{step length along the direction } \nabla J \] Optimal value can be obtained by Armijo-Wolfe conditions

Orbit Circle Guidance at Final Steady-Stage

\[
u(t) = \begin{cases} 
\dot{\psi}_{com}(t) = \dot{\psi}_{ss} & \text{if } |\dot{\psi}_{com}(t) - \dot{\psi}_{ss} = v / R_{ss}| \leq \varepsilon_{ss} \\
\dot{\psi}_{com}(t) = \dot{\psi}_{ss} + \mu \alpha(t) \dot{\psi}(t) & \text{other}
\end{cases}
\]

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

\[R_{ss} = v / \dot{\psi}_{ss} : \text{a final approach circle radius.} \]
Milestones

- Motivations
- Communication Modeling
- Self-Tuning Extremum Control
- Flight Test Results
Rapid Flight Test Design Keys
- Reduce development time
- Upgrade is flexible
- Convenience of high level programming
Model Verification Flight Test

3 dB Omni-Directional Antenna

9 dB Sector Antenna
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
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

Sensor Node Locations & Flight Setup in Camp Roberts

GCS

[Map Image with coordinates and distances]
UAV Trajectory over SNR MAP

UAV Trajectory Control for Max Communication Links (SNR)
UAV Path over SNR Map

Plot of UAV Trajectory over SNR Maps
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-line 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