에어노드 기반 무선센서네트워크 구축을 위한 적응형 오르막경사법 기반의 자율무인비행로봇제어

Autonomous Unmanned Flying Robot Control for Reconfigurable Airborne Wireless Sensor Networks Using Adaptive Gradient Climbing Algorithm

이 덕 진[1]

Deok-Jin Lee[1]

Abstract This paper describes efficient flight control algorithms for building a reconfigurable ad-hoc wireless sensor networks between nodes on the ground and airborne nodes mounted on autonomous vehicles to increase the operational range of an aerial robot or the communication connectivity. Two autonomous flight control algorithms based on adaptive gradient climbing approach are developed to steer the aerial vehicles to reach optimal locations for the maximum communication throughputs in the airborne sensor networks. The first autonomous vehicle control algorithm is presented for seeking the source of a scalar signal by directly using the extremum-seeking based forward surge control approach with no position information of the aerial vehicle. The second flight control algorithm is developed with the angular rate command by integrating an adaptive gradient climbing technique which uses an on-line gradient estimator to identify the derivative of a performance cost function. They incorporate the network performance into the feedback path to mitigate interference and noise. A communication propagation model is used to predict the link quality of the communication connectivity between distributed nodes. Simulation study is conducted to evaluate the effectiveness of the proposed reconfigurable airborne wireless networking control algorithms.

Keywords: Unmanned Flying Robots, Adaptive Gradient Climbing, Reconfigurable Airborne Sensor Networks, Communication Relay, Autonomous Flight Control

1. Introduction

In recent years, wireless sensor networks have become an attractive emerging technology in a wide variety of applications.[1,2] In future wireless sensor network environment, teams of heterogeneous autonomous vehicles will be deployed in a cooperative manner to conduct a broad range of applications; wide-area sensing, surveillance, search and rescue

missions in various environments.[2,3] The operational range of cooperating mobile agents is limited by the communication range of a single agent. A linked network chain of airborne mobile nodes increases the communication range between a remote sensing node and ground nodes. Under this operational concept, unmanned aerial vehicles could play an important role of communication relaying nodes. In this paper, wireless ad-hoc sensor networks consisting of ad-hoc nodes on the ground and airborne ad-hoc mobile nodes mounted in small flying robots is considered, and two scenarios are envisioned for the application in Figs. 1 and 2. In the first scenario, the airborne nodes on flying robots maintain connectivity to the

Fig. 1. Airborne wireless sensor networks using aerial robots as communication relay nodes to increase ground node connectivity

Fig. 2. Airborne relay sensor networks between distributed airborne mobile nodes and a ground node to increase the mission range of autonomous flying robots

ground nodes which are disconnected due to distance and/or terrain as a communication relay. In the second, an aerial vehicle has constrained operational range due to limited communication range. A communication relaying technique between multiple networked flying robots extends communication range, which in turn increases the operational range of the aerial vehicle.

The concept of communication relay nodes using unmanned aerial vehicles (UAVs) was proposed in the literature[4] where the UAVs are used as platforms for a high capacity radio relay and broadcast system. More research has been conducted on this type of the communication networks[5,6]. Horner and Healey[5] proposed an artificial potential field based sliding mode controller for high bandwidth wireless communication networks between UAVs

and autonomous surface vehicles (ASVs) using a static source searching approach with a deterministic potential function. Frew and his colleagues[6] have conducted research on this topic and developed a Lyapunov guidance vector field (LGVF) based control algorithm in order to control the UAV positioning to optimize communication links. In the research, the optimal positioning control for airborne sensor networks was demonstrated with a circular motion control which is impractical to UAV operation, leading to very expensive costs in terms of endurance time and fuel consumption, and simulation studies and data analysis was conducted based on the data collected by flying aerial vehicles remotely without direct autonomous UAV positioning flight control.

The contribution of this paper is efficient autonomous flying vehicle control algorithms for a reconfigurable ad-hoc wireless airborne sensor networks to increase the operational range of an aerial robot or the communication connectivity between them as described in Figs 1 and 2. Two autonomous flight control algorithms based on adaptive gradient climbing approach[7] are developed to steer the aerial vehicles to reach an optimal location for the maximum communication throughputs. The first autonomous vehicle control algorithm is presented for seeking the source of a scalar signal by directly using an extremum-seeking[8] based forward velocity control with a constant angular rate with no position information of the aerial vehicle. The second flight control algorithm is developed with the angular rate command by integrating an adaptive gradient climbing technique which uses an on-line gradient estimator to identify the derivative of a performance cost function. They incorporate the network performance into the feedback path to mitigate interference and noise. Incorporating the network performance into the feedback path, communication physical layer effects such as interference, noise, signal attenuation, and transmission power decay can be mitigated.

The flight controller onboard the aerial vehicle uses some scalar signal which could be an electromagnetic, acoustic, or radar signal emanating from the source it seeks. The scalar signal used in this paper is the value of a signal-to-noise ratio (SNR) which is a function of the location of the sensor nodes, the UAV position, and the attitude of the UAV, and the strength of the signal decays away from the source through diffusion or other uncertain dynamic environment.

The remainder of this paper is organized as follows.

Section 2 describes the development of the adaptive gradient climbing control approach. In Section 3 a communication propagation model is described. In Section 4 two autonomous flight control algorithms for optimal localization of the flying robot to obtain maximum network connectivity are presented. Section 5 presents various simulation results. Conclusion and discussion is presented in section 6.

2. Adaptive Gradient Climbing Control

In this section, an adaptive gradient climbing control algorithm which allows aerial vehicles to reposition themselves autonomously to maintain optimal loitering flight paths to establish stable communication links between ground nodes and remote nodes on aerial vehicles is described.

2.1 Gradient Climbing Algorithms

In this section, a deterministic hill-climbing type gradient control is briefly reviewed.[10] Assume that the nonlinear dynamic and measurement model is expressed by

$$\begin{aligned} \mathbf{x}_{k+1} &= \mathbf{f}(\mathbf{x}_k, \mathbf{u}_k) \\ z_k &= J_k(\mathbf{x}_k) \end{aligned} \tag{1}$$

where $\mathbf{x}_k \in \Re^n$ is the n-dimensional state, given $\mathbf{f} : \Re^n \to \Re^n$, $\mathbf{u}_k \in \Re^l$ is the control input, and $z_k \in \Re$ is a scalar measurement cost function with $J : \Re^n \to \Re$. Based on the information measurement expressed by a deterministic loss function $J = L(\mathbf{x}) : \Re^n \to \Re$, a gradient climbing controller is expected to regulate the state as guided by the search sequence, and in turn maximize the performance output or minimizes the cost output. The gradient climbing control is interpreted as the following optimization problem

$$\begin{aligned} &\min_{\mathbf{x}_k \in D} J_k(\mathbf{x}_k) \\ &\text{subject to } \mathbf{x}_{k+1} = \mathbf{f}(\mathbf{x}_k, \mathbf{u}_k) \end{aligned} \tag{2}$$

where $\mathbf{u}_k \in \Re^n$ is a control input. For a gradient based search method, each iteration of a search loop computes a direction of the state and the extremum search provides the following[10]

$$\begin{aligned} \mathbf{x}_{k+1} &= \mathbf{x}_k + \alpha_k \mathbf{d}_k \\ &= \mathbf{x}_k - \alpha_k \mathbf{B}_k \nabla J(\mathbf{x}_k) \end{aligned} \tag{3}$$

where $\mathbf{d}_k \equiv -\mathbf{B}_k \nabla J(\mathbf{x}_k)$ decides the direction of the search and is required to be a descent/ascent direction which allows the

cost function J_k to be either reduced or increased gradually along the direction, and $\alpha_k > 0$ is the step length along the direction $\mathbf{d}_k$. $\mathbf{B}_k$ is a suitable approximation of the Hessian matrix $\nabla^2 J(\mathbf{x}_k)$. For the case of $\mathbf{B}_k = \mathbf{I}$, the above optimization method is referred to the gradient method or steepest descent method, $\mathbf{d}_k = -\nabla J(\mathbf{x}_k) = \partial J(\mathbf{x}_k) / \partial \mathbf{x}_k$. The key in this gradient control approach is the computation of the gradient of the cost function using either an analytical method or numerical way. In the next subsection, we introduce a numerical gradient estimator with no mathematical model of the cost function.

2.2 Derivative-Free Adaptive Gradient Estimation

When the analytical model of the loss function is not available or feasible to calculate the derivative of the function, a derivative-free gradient estimator, called the extremum-seeking (ES) approach[8], can be applied to calculate the gradient in a numerical way without analytical expressions. The ES algorithm is an adaptive and model-free gradient estimator providing quantitative gradient values in a numerical way without calculating the analytical derivatives of the cost function. The typical architecture of the ES approach is composed of four elements, a high pass filter, a low pass filter, demodulation, and perturbation, as shown in Fig. 3.

For understanding of the architecture of the ES method, a brief mathematical description is introduced to explain how to estimate the gradient of a cost function. Suppose $\hat{\theta}$ is assumed to be the current value of the parameter, and $a \sin wt$ is a small sinusoidal perturbation around $\hat{\theta}$. Then the output of the objective function is expressed by[8]

$$z = J(\hat{\theta} + a \sin wt) \approx J(\hat{\theta}) + a \frac{\partial J}{\partial \theta}\bigg|_{\theta = \hat{\theta}} \sin wt \tag{4}$$

Fig. 3. Typical architecture of the extremum-seeking (ES) algorithm for gradient estimation

where constant term in the output z is removed by applying a high-pass filter (HPF) as a differentiator

$$z_H \approx a \frac{\partial J}{\partial \theta}\bigg|_{\theta=\hat{\theta}} \sin wt \tag{5}$$

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

$$\varepsilon = \frac{1}{2}a \frac{\partial J}{\partial \theta}\bigg|_{\theta=\hat{\theta}} - \frac{1}{2}a \frac{\partial J}{\partial \theta}\bigg|_{\theta=\hat{\theta}} \cos 2wt \tag{6}$$

Low-pass filtering of the demodulated the signal, ε, provides an estimate of the local gradient of $J(\theta)$

$$z_L \approx \frac{1}{2}a \frac{\partial J}{\partial \theta}\bigg|_{\theta=\hat{\theta}} \tag{7}$$

The estimated gradient can be approximated in terms of the parameter change as

$$\nabla \hat{J} \equiv \zeta z_L = \zeta \frac{1}{2}a \frac{\partial J}{\partial \theta}\bigg|_{\theta=\hat{\theta}} \tag{8}$$

where ζ is a design parameter to be adjusted. The gradient estimate is then used to update the parameter by feeding back to a compensator to control the dynamic plant. See Ref. [8] for more detail regarding the proof of stability and design guidelines.

2.3 Adaptive Gradient Climbing Control

It is noted that for the case where the analytical differential model of the loss function or the gradient calculation is not feasible, the ES technique can be an alternative way to computing the gradient estimate in a numerical way. Based on the idea of the ES approach, an adaptive gradient climbing control method is designed by integrating the gradient climbing algorithm with the derivative-free numerical gradient estimator. The overall structure of the proposed self-estimating adaptive gradient climbing controller (AGCC) is illustrated in Fig. 4.

As can be seen in the above AGCC architecture, the estimated gradient of the cost function is obtained by applying the ES algorithm, and then a compensator is designed for each specific control of a dynamic plant by taking the

Fig. 4. Adaptive gradient climbing control (AGCC) architecture with derivative-free gradient estimator

estimated gradient. Finally, combing the ES gradient estimator with the gradient climbing control method, the derivative-free adaptive gradient climbing control can be expressed by

$$\hat{\mathbf{x}}_{k+1} = \hat{\mathbf{x}}_k - \alpha_k \frac{\partial J}{\partial \mathbf{x}}\bigg|_{\mathbf{x}=\hat{\mathbf{x}}_k} = \hat{\mathbf{x}}_k - \alpha_k \nabla \hat{J}(\hat{\mathbf{x}}_k)$$
$$\approx \hat{\mathbf{x}}_k - \alpha_k \left(\zeta \frac{1}{2}a \frac{\partial J}{\partial \mathbf{x}}\bigg|_{\mathbf{x}=\hat{\mathbf{x}}_k} \right) \tag{9}$$

where $\nabla \hat{J} \in \Re^n$ denotes the estimated gradient of the loss function at time k, and $\hat{\mathbf{x}}_k \in \Re^n$ denotes the parameter estimate. The performance of the adaptive gradient climbing controller is subject to random noise which may be included in the cost function information. When the measurements of the cost function used in the gradient estimation include noise or uncertainty, a low-pass filter can be applied as a pre-processing means before estimating the gradient of the noise measurement of a cost function. On the other hand, a stochastic gradient climbing algorithm for noisy measurements can also be used by either using the finite-difference stochastic approximation (FDSA) or the simultaneous perturbation stochastic approximation (SPSA)[9]. Both methods are also based on derivative-free gradient estimation in a numerical way and details of the stochastic approaches can be referred to in [9].

3. Communication Propagation Model

In this section, a communication propagation model which predicts the signal-to-noise ratio (SNR) as a measure of the ratio between the received power and the noise power is introduced (refer to [7] for detail). The equations for the signal-to-noise ratio (SNR) is expressed by

$$\mathrm{SNR}(dBm) = \frac{P_r(dBm)}{P_n(dBm)} = (\frac{\lambda}{4\pi\|\mathbf{d}(t)\|})^2 \frac{G_t G_r}{L_{ap}(t)} \qquad (10)$$

where $P_r(dBm)$ is the receiver power, $P_n(dB)$ is noise power (-95 dBm), $G_t(dB)$ is transmitter antenna gain (14 dB), $G_r(dB)$ is receiver antenna gain (2.2 dB), $L_p(dB) \equiv (4\pi\|\mathbf{d}(t)\|/\lambda)^2$ is path loss which denotes the loss associated with propagation of electromagnetic waves, $\|\mathbf{d}(t)\|$ is the relative distance in km between the aerial node and ith remote sensor node. $L_{ap}(dB)$ is antenna pattern loss, $\lambda = c/f$ where f is the transmission frequency in Hz and $c = 3 \times 10^8$ m/s.[11]

Straight forward method to define a figure of merit of the cost function in distributed multiple sensor nodes is to calculate an average value by adding all of each SNR_i function with a proper weight value $\mathcal{W}_i$

$$J(t) = \sum_{i=1}^{N} \mathcal{W}_i SNR_i(t) = \sum_{i=1}^{N} \mathcal{W}_i J_i(t), \text{ and } \sum_{i=1}^{N} \mathcal{W}_i = 1 \qquad (11)$$

where N is the number of the sensor nodes consisting of a wireless communication sensor networks, and SNR_i is computed by using [10] with information from neighboring distributed remote nodes and the airborne sensor node. For the noisy measurement of the loss function, the measurement equation can be written as

$$z(\mathbf{x}, v) = J(\mathbf{x}) + v = \sum_{i=1}^{N} \mathcal{W}_i SNR_i(t) + v, \quad i = 1, \ldots, N \qquad (12)$$

where $v \in \Re^1$ is the white Gaussian noise term.

4. Autonomous UAV Flight Control

In this section, we present autonomous flight control algorithms for aerial vehicle to build an ad-hoc communication sensor networks between aerial nodes and nodes on the ground. It is assumed that the ad-hoc networking allows any two nodes to communicate either directly or through an arbitrary number of other nodes which act as relays.

4.1 Flying Vehicle Model for Autonomous Flight Controls

Suppose that $\mathbf{p}(t) = [x(t), y(t), z(t)]^T \in \Re^3$ presents the UAV trajectory resolved in the local tangent coordinates (East, North, Down), then the fixed-wing aerial vehicle can be described by[12]

$$\begin{aligned}
\dot{x}(t) &= v\cos\gamma\cos\psi \\
\dot{y}(t) &= v\cos\gamma\sin\psi \\
\dot{h}(t) &= v\sin\gamma \\
\dot{v}(t) &= \frac{T\cos\alpha - D}{m} - g\sin\gamma \\
\dot{\gamma}(t) &= \frac{T\sin\alpha + L}{mv}\cos\phi - \frac{g}{v}\cos\gamma \\
\dot{\psi}(t) &= \frac{T\sin\alpha + L}{mv}\frac{\sin\phi}{\cos\gamma}
\end{aligned} \qquad (13)$$

where $v \in \Re^1$ is the ground speed and is assumed to be equal to the airspeed, $T \in \Re^1$ is the engine thrust, $\alpha \in \Re^1$ is the angle of attack, $D \in \Re^1$ is the aerodynamic drag, $L \in \Re^1$ is the lift force, $m \in \Re^1$ is the mass of the flying vehicle, $g \in \Re^1$ is the gravity constant, $\gamma \in \Re^1$ is the flight path angle, $\phi \in \Re^1$ is the bank angle, and $\psi \in \Re^1$ is the heading angle.

Suppose that the altitude variation is not considered with the flight path angle close to zero, i.e., $\gamma \approx 0$. The equations of motion of the flying vehicle reduce to the following planar motion

$$\begin{aligned}
\dot{x}(t) &= u_1\cos\psi \\
\dot{y}(t) &= u_1\sin\psi \\
\dot{\psi}(t) &= u_2
\end{aligned} \qquad (14)$$

where $u_1 \in \Re^1 \equiv v$ and $u_2 \in \Re^1 \equiv (T\sin\alpha + L)\sin\phi/mv$. For the case of the constant angle of attack with a small value, the equation of motion can be further simplified by

$$\begin{aligned}
\dot{x}(t) &= v\cos\psi \\
\dot{y}(t) &= v\sin\psi \\
\dot{\psi}(t) &= v\kappa
\end{aligned} \qquad (15)$$

where $\kappa \in \Re^1$ is a bounded curvature. From the above equation, the control inputs $\mathbf{u} \in \Re^2 = (u_1 = v, u_2 = \dot{\psi})^T$ can be the heading and the speed. The relation of the heading and the bank angle is represented by

$$\phi(t) = \tan^{-1}\left(\frac{v^2}{gR}\right) = \tan^{-1}\left(\frac{v}{g}\dot{\psi}(t)\right) \qquad (16)$$

where the $R \in \Re^1$ is the radius of a curvature, and have the relationship with the speed and the heading rate, $v/R = \dot{\psi} \in \Re^1$. The heading is defined as the heading of the UAV with respect to the positive x-axis.

4.2 Autonomous Flying Vehicle Localization with Surge Control

An autonomous vehicle control algorithm is presented for seeking the source of a scalar signal such as a wireless communication signal by using the speed and heading rate as control inputs. The flight control algorithm is designed directly by using the extremum-seeking based forward surge control approach with no position information of the aerial robot.

Assume that the nonlinear flight model is expressed by the non-holonomic shown in [15], the angular velocity input $\dot{\psi} = w \in \Re^1$ be constant. The velocity control input $u(t) \equiv v(t)$ is composed of a constant, mean velocity and a sinusoidal velocity perturbation[8]

$$v(t) = aw + 2\sqrt{\alpha^2(t) + \beta^2(t)} \sin\left(wt + \tan^{-1}\left(\frac{\alpha(t)}{\beta(t)}\right)\right) \quad (17)$$

where $a \in \Re^1$ is a constant value, $\alpha(t) \in \Re^1$ and $\beta(t) \in \Re^1$ are the parameters that are needed to be tuned by the extremum-seeking (ES) technique. The control architecture of the ES algorithm is depicted in Fig. 5.

In the control architecture, $C_x \in \Re^1$ and $C_y \in \Re^1$ are the gain values needed to be tuned, $w_h \in \Re^1$ is the frequency for the high pass filter to be selected in the ES, respectively.

For the evaluation of the effectiveness of the proposed adaptive forward surge control, a simulation study with application to searching a static source is investigated with no position information of the flight vehicle. The strength of the signal is assumed to be decay away from the source through

diffusion or other dynamic environments. The flying robot could only sense the strength of the signal at the location of it sensor. To locate the vehicle to the source, the ES-based flight control technique is applied by using [17]. The initial starting location of the aerial vehicle is $\mathbf{p}(t_0) = [800, 20, 600]^T \in \Re^3$, the frequency for the high pass filter is $w_h = 0.1$, the gain values for the forward speed control are $C_x = 0.15$ $C_y = 0.15$, the constant parameter $a = 1.0$, the frequency for the sinusoidal is set to $w = 0.1$, and the constant angular velocity is $w = 10 \deg/\sec$.

Fig. 6 shows the flight trajectory of an aerial vehicle for seeking a source of a scalar signal observation without knowing position information of the flying robot, and the convergence of the source seeking is made at the final position $\mathbf{p}(t_f) = [790, 34, 600]^T \in \Re^3$ which is the location of the source. After reaching the location of the source, it flies around the location with a constant orbit radius to provide continuous information of the source.

Fig. 7 is the plot of the strength of the source signal as the function of time, and it reaches the maximum with a

Fig. 6. Autonomous localization of the flying vehicle for the source seeking of a scalar signal with no information of the flying vehicle position information

Fig. 7. Plot of the SNR signal strength of the cost function as the function of the time

Fig. 5. Autonomous flying robot localization using the adaptive surge control for seeking the source of a scalar communication signal with no position information

converged value at 34.6 dB. It indicates that the surge forward speed control with a constant heading rate steers the flying robot to the maximum source location with a scalar measurement.

4.3 Autonomous Flying Vehicle Localization with Heading Rate Control

For some vehicles including fixed-wing flying vehicle, the surge control with a constant heading rate can not realistically be applied. Therefore, a complementary flight control case with a constant forward velocity but tuned angular velocity is introduced by using the proposed adaptive gradient climbing technique in 2.3.

For the sake of simplicity, it is assumed that the cost function or the strength of the source signal $J(t) \in \Re^1$ is computed by using a signal-to-noise ratio (SNR) model explained in [11]. Thus the SNR performance function is a nonlinear function of several variables such as the relative distance between an aerial vehicle and remote nodes on the ground, as well as orientation angles of the aerial vehicle in flight. First, it is assumed that the UAV has a constant speed command with a level flight ($\dot{v} = 0$, and $\dot{h}(t) = 0$, where h is the altitude above the mean sea level). In this case, the heading angle or rate is the only control variable, and the commanded control input is expressed in terms of a heading rate command, $u_{com}(t) = v\kappa = \dot{\psi}_{com}(t)$. Now, based on the constraint of constant speed with straight level flight, the components of the UAV position vector in [15] become an implicit function of the heading angle only, $x(t) = f_1(\psi(t)), y(t) = f_2(\psi(t))$, the cost function in the optimization can be written as an implicit function of the heading angle only, $J(x(t), y(t), h(t)) = J(\psi(t))$, which reduces the multiple dimensional gradient calculation to a scalar one. Specifically, following the gradient climbing approach, the descent direction of $\mathbf{d}_k$ becomes equal to $\mathbf{d}_k = \nabla J(\mathbf{x}_k) = \partial J(t) / \partial \psi(t)$.

As explained, it is noted that the gradient estimate of the cost function is obtained by utilizing the numerical ES approach[7] instead of applying a direct analytical derivation method. The heading control for an UAV flight control can be decided by utilizing the gradient method by replacing the general state vector with the heading angle $\mathbf{x}_k \equiv \psi_k \in \Re^1$ as

$$\psi_{k+1} = \psi_k + \alpha_k \nabla \hat{J}_\psi \tag{18}$$

where α_k is the step-length parameters which can be either constant or time-varying, and it is assumed that the gradient estimate, $\nabla \hat{J}_\psi = \partial J(t) / \partial \psi(t) \in \Re^1$, can be obtainable from the peak-seeking approach explained in the previous subsection. Now rearranging the above equation gives

$$\psi_{k+1} - \psi_k = \alpha_k \nabla \hat{J}_\psi$$
$$\nabla \psi = \alpha_k \nabla \hat{J}_\psi \tag{19}$$

Assuming the variation of the heading angle and the cost function at each time is small, and taking the derivative of the variation terms on both sides of Eq. (18) leads to the following relation

$$\frac{d\psi(t)}{dt} = \alpha(t) \frac{d}{dt} \left(\nabla \hat{J}_\psi \right) \tag{20}$$

It is assumed that the characteristics of the figure of merit of the cost function is quadratic in terms of the heading angle variable, then the performance function can be expressed by

$$\tilde{J}(\psi(t)) = J^* + \frac{\mu}{2} \left(\hat{\psi}(t) - \psi^* \right)^2 + v(t)$$
$$= J(\hat{\psi}(t)) + v(t) \tag{21}$$

where $\tilde{J}$ is the observed sensor measurement, J^* is the maximum attainable value of the cost function, ψ^* is the heading angle which maximizes the performance function, $\hat{\psi}(t)$ is the current heading angle estimate, and μ is the sensitivity of the quadratic curve which relates heading angle to the indicated SNR, and $v(t)$ is a noise term which can be smoothed out by applying a proper low-pass filter. It is assumed that the parameters which characterize the optimum values are unknown, but constant parameters. Taking a gradient of the cost function with respect to the current estimate $\hat{\psi}(t)$ provides the following

$$\nabla \hat{J}_{\hat{\psi}(t)} \equiv \frac{\partial J(\hat{\psi}(t))}{\partial \hat{\psi}(t)} = \mu \left(\hat{\psi}(t) - \psi^* \right) \tag{22}$$

Taking a time derivative of the above gradient term again leads to

$$\frac{d}{dt} \left(\nabla \hat{J}_{\hat{\psi}(t)} \right) = \mu \left(\dot{\hat{\psi}}(t) \right) \tag{23}$$

Finally, substituting Eq. (23) into Eq. (20) gives the heading-rate control command as

$$\dot{\psi}_{com}(t) = \frac{d\psi(t)}{dt} = \alpha(t)\frac{d}{dt}\left(\nabla\hat{J}_{\hat{\psi}(t)}\right) \qquad (24)$$
$$= \mu\alpha(t)\dot{\hat{\psi}}(t)$$

Note that the rate of the estimate of the current heading angle $\dot{\hat{\psi}}(t)$ can be obtained from [8] after applying the low-pass filter in the process of the ES loop.

At the final stage of the communication network control, the UAV reaches the optimal location, it is necessary to make the UAV fly around the set point rather than fly directly to the point or pass over the point. Thus a steady-state heading $\dot{\psi}_{ss}$ is introduced to guarantee that the UAV will orbit with a constant radius R_{ss} at the final stage. The heading-rate command is rewritten by

$$\dot{\psi}_{com} = \dot{\psi}_{ss} + \mu\,\alpha(t)\dot{\hat{\psi}}(t) \qquad (25)$$

where ψ_{ss} is a steady-state heading input to be selected and is related to a final approach circle radius, $R_{ss} = v/\dot{\psi}_{ss}$. Finally, the autonomous flight control input $u(t) \equiv \dot{\psi}_{com}(t)$ to the UAV using the heading-rate command in [18] is expressed by

$$u(t) = \begin{cases} \dot{\psi}_{com}(t) = \dot{\psi}_{ss}, \ if \ \left|\delta\dot{\psi}_{com} = v/R_{ss}\right| \le \varepsilon_{ss} \\ \dot{\psi}_{com}(t) = \dot{\psi}_{ss} + \mu\,\alpha(t)\dot{\hat{\psi}}(t), otherwise \end{cases} \qquad (27)$$

where ε_{ss} is a criterion which guarantees the bounded motion of the UAV at the final stage, and $\delta\dot{\psi}_{com}(t) \equiv \dot{\psi}_{com}(t) - \psi_{ss}$. To make its convergence faster, the time-step scaling factor α_k is computed by using a more intuitive method and the adaptive time-step α_k is computed by

$$\alpha_{k+1} = \gamma\alpha_k, \ where \begin{cases} 0 < \gamma < 1, \ if \ \Delta J_{k+1} > \tau_{tv} \\ \gamma \ge 1, \quad else \ \Delta J_{k+1} < \tau_{tv} \end{cases} \qquad (28)$$

where $\Delta J_{k+1} \equiv J_{k+1} - J_k$, τ_{tv} is a specified threshold value, and $\gamma > 0$ is an user design factor to be selected.

5. Simulation Results

The designed autonomous flight control algorithms with the angular rate control approach with application to a high bandwidth communication networks between multiple nodes on the ground and sensor nodes on aerial vehicles have been tested via hardware-in-the-loop simulations (HILS) as shown in Fig. 8. The detail of the HILS setup is referred to [13].

We consider an-hoc networks consisting of ad-hoc nodes

on the ground and ad-hoc nodes mounted in the unmanned aerial vehicles and assume that all nodes whether on the ground or mounted in a UAV use the same core mesh network radio. The mobility of aerial nodes is modeled as the standard bicycle kinematic model and the proposed communication model of the SNR measurement is used to predict the communication throughputs between the UAV and other remote nodes on the ground sending signals to the UAV based on the ad-hoc communication.[11]

In the first HILS test, the initial starting location of the Rascal UAV is given at ($x_0 = 10\,m, y_0 = 0\,m, h = 600\,m$) in East, North, and Down directions, and the speed is fixed at $v = 20\,m/s$. The aerial vehicle is flying with a fixed altitude at h=600 m, and nodes on the ground are assumed to be static and the locations of the nodes are set at
($x_{node,1} = -1000\,m, y_{node,1} = 614.5\,m, z_{node,1} = 5\,m$)
($x_{node,2} = 3500\,m, \ y_{node,2} = 114.5\,m, z_{node,2} = 5\,m$)

Fig. 9 describes the SNR signal distribution in 3-D space which is generated by fusing the throughputs from the two

Fig. 8. Architecture for hardware-in-the-loop simulation setup for the autonomous flying vehicle control using the adaptive gradient climbing with the heading rate control technique.

Fig. 9. 3D map of SNR distribution by fusing the communication signals from two remote nodes on the ground

antenna nodes based on [12]. The maximum SNR location that UAV should reach and loiter is depicted in red color with a bell shape.

Fig. 10 describes the trajectory of the aerial robot in the local tangent frame (NED frame), and initially it is located around the origin and starts moving forward to the middle and intersection point between the two remote ground nodes. After approached near optimal set point, it changes from a flying mode into an orbiting one with a constant radius following the commands from the steady-state heading rate using [27]. As expected the optimal deployment of the aerial vehicle for high band communication links lies on the line of the intersection area between the two nodes.

The primary goal of the next simulation study is to verify the performance of the adaptive gradient-climbing for distributed multiple sensor nodes for robust long-range and/or wide-coverage wireless communication networking for more sophisticated surveillance and searching missions. The overall concept of aerial wireless sensor networking from distributed nodes is described in Fig. 11.

Fig. 12 shows the flight trajectory of a UAV for high bandwidth communication link quality connecting with five remote nodes on the ground. The starting point of the UAV is (1200 m - East, 1200 m - North) and the converged optimal location is next to the origin (0 m - East, 0 m - North). The color of the UAV trajectory indicates the SNR signal strength of the distributed sensor networks. It can be seen that the optimal link location resides inside the intersection area of all

Fig. 11. Concept of high bandwidth wireless communication networks between an aerial node and distributed multiple ground nodes using vehicle as a relay node

Fig. 12. An illustration of the flight control using the adaptive gradient climbing technique for deployment of a UAV to localize a UAV for maximum communication signal throughputs with distributed multiple ground nodes

the communication contours.

A plot of the SNR signal strength between the aerial vehicle and the five remote nodes is provided in Fig. 13 with uneven power distributions. As you can see the communication throughputs have converged to a value of 33 dB after the aerial robotic vehicle reached the final location, which indicate the quality of communication links between the distributed sensor nodes is maximized. The slight variation in the converged SNR value is due to the UAV orbiting motion with a constant radius. This simulation demonstrates that the adaptive gradient climbing based autonomous flight control algorithm can be

Fig. 10. Flight trajectory of an aerial robot for building high bandwidth communication networks between two remote nodes. The UAV is directed by the estimated information gain gradient and observation information.

Fig. 13. Signal strength of the wireless communication between the UAV aerial node and five remote nodes on the ground through the aerial relay node

used to allow aerial vehicles to find the maximized communication link quality. As opposed to extending the end-to-end throughput of a communication chain, the relay nodes could optimize wide network coverage for a series of dispersed nodes.

An application where this setup would be useful is when a series of users, such as mobile robots on ground or autonomous surface vehicles in ocean need to communicate, but have no line-of-sight contact with other users.

6. Conclusion

This paper described an efficient implementation of a reconfigurable dynamic ad-hoc wireless communication network between nodes on the ground and mobile nodes mounted on autonomous vehicles to increase the operational range of an end-node aerial robot or the communication connectivity between them. Two autonomous flight control algorithms were developed to steer the aerial vehicles to reach an optimal location for the maximum communication throughputs among nodes. The first autonomous vehicle control algorithm is presented for seeking the source of a scalar signal by directly using the ES based forward surge control approach with no position information of the aerial robot. The second flight control algorithm was developed with the angular rate using the adaptive gradient climbing technique which uses an on-line gradient estimator to identify the derivative of a performance

cost function, and it incorporates the network performance into the feedback path to mitigate interference and noise. The hardware-in-the-loop simulation experiments successfully demonstrated the effectiveness of the adaptive gradient control algorithm for building robust distributed wireless communication networks which increases the operational range of unmanned aerial vehicles.

Acknowledgements

References

[1] D. A. Schoenwald, "AUVs: In Space, Air, Water, and on the Ground," IEEE Control Systems Magazine, Vol.20, No.6, pp.15-18, Dec. 2000.

[2] C.-Y. Chong, and S. P. Kumar, "Sensor Networks: Evolution, Opportunities, and Challenges," Proceedings of the IEEE, Vol.91, No.8, pp.1247-1256, Aug. 2003.

[3] P. Ögren, E. Fiorelli, and N. Ehrich, "Cooperative Control of Mobile Sensor Networks: Adaptive Gradient Climbing in a Distributed Environment," IEEE Transactions on Automatic Control, Vol.49, No.8, pp.1292-1302, Aug. 2004.

[4] P. Basu, J. Redi, and V. Shurbanov, "Coordinated Flocking of UAVs for Improved Connection of Mobile Ground Nodes," Proceedings of the IEEE Military Communications Conference, pp.1628-1634, 2004.

[5] D. P. Horner, and A. J. Healey, "Use of Artificial Potential Fields for UAV Guidance and Optimization of WLAN Communications," Proceedings of the 2004 IEEE/EOS Autonomous Underwater Vehicles Conference, Maine, pp.88-95, June 2004.

[6] E. W. Frew, and T. X. Brown, "Airborne Communication Networks for Small Unmanned Aircraft Systems," Proceedings of the IEEE, Vol.96, No.12, Dec. 2008.

[7] D.-J. Lee, and R. Mark, "Decentralized Control of

Unmanned Aerial Robots for Wireless Airborne Communication Networks," International Journal of Advanced Robotic Systems, Vol.7, No.3, pp.191-200, 2010.

[8] K. B. Ariyur, and M. Krstic, Real-Time Optimization by Extremum Seeking Control, Hoboken, NJ, John Wiley & Sons, Inc., 2003.

[9] J. C. Spall, An Introduction to Stochastic Search and Optimization: Estimation, Simulation, and Control, Hoboken, NJ, John Wiley & Sons, Inc., 2003.

[10] A. Quarteroni, R. Sacco, and F. Saleri, Numerical Mathematics, New York, NY, Springer-Verlag, Inc., 2002.

[11] T. S. Rappaport, Wireless Communications: Principles and Practice, 2nd ed., Upper Saddle River, N.J., Prentice Hall PTR, 2002.

[12] B. L. Stevens, and F. L. Lewis, Aircraft Control and Simulation, 2nd ed., Hoboken, N.J., John Wiley & Sons, Inc., 2003.

[13] D.-J. Lee, I. Kaminer, K. D. Jones, and V. Dobrokhodov, "Autonomous Feature Following for Visual Surveillance Using a Small Unmanned Aerial Robot with a Gimbaled Camera," International Journal of Control, Automation, and Systems, Vol.8, No.5, pp.957-966, Oct. 2010.

[14] J. Cochran, and M. Krstic, "Nonholonomic Source Seeking with Tuning of Angular Velocity," IEEE Transactions on Automatic Control, Vol.54, No.4, pp. 717-731, April 2009.

Lee Deok Jin

1999 Texas A&M University, Aerospace Engineering (M.S.)
2005 Texas A&M University, Aerospace Engineering (Ph.D.)
2010~Current Senior Researcher, UAV Flight Control Group, Korean Air R&D Center, Adjunct Assistant Professor, Dept. of Electronics & Information Engineering Division, Chonbuk National University.
Research Area: Autonomous Unmanned Systems, Adaptive Control, Reconfigurable Airborne Wireless Sensor Networks, Cooperative Control of Networked Multiple Vehicles, Distributed Sensor Fusion.