Proceedings of the 17th World Congress
The International Federation of Automatic Control
Seoul, Korea, July 6-11, 2008

Simple Altitude Estimator using Air-Data and GPS Measurements

Ick-Ho Whang, Won-Sang Ra

Guidance and Control Department, Agency for Defense Development,
B.O.Box 35-11, Yuseong, Daejeon, 305-600, Korea
(Tel: +82-42-821-4413; e-mail:{ickho,wonsang }@ add.re.kr).

Abstract: For obtaining the height information, a vertically damped inertial navigation system (INS) using the height reference of barometer measurements is conventionally instrumented. Since it requires delicate construction of INS system, in many cases, it has been costly. In this paper, a novel altitude estimation system is proposed by effectively combining the information of the GPS height and air data measurements such as ambient air pressure and temperature. Based on the fact that the barometer errors mainly consist of bias and scale factor errors, a filter to estimate the bias and scale factor using the GPS height is derived by means of multiple hypothesis Gaussian approximation filter technique. The estimated bias and scale factor is used to compensate the baro-altitude. Simulation results show that this method can construct a good altitude measurement system with relatively low cost.

1. INTRODUCTION

For successful design of unmanned air vehicles (UAVs) performing missions in low altitude, it is very important to provide height information not so costly. Conventional solutions for this problem are barometer aided inertial navigation system (INS) and its variations. The main idea is to construct a stable INS vertical channel by means of height error damping loops with the reference of barometer height measurements. This method is reported to be able to continuously provide the height information in spite of adverse environment such as jamming, or large attitude angle of the UAV. However, since this method requires expensive sophisticate inertial sensor systems, it is not easy to construct an altitude sensing system in low cost.

Nowadays the development of global positioning system (GPS) has changed the general concept of navigation system. As GPS becomes available in very low cost, many UAV systems include GPS receivers to provide low-cost navigation solutions with fairly good error performance. However, there are some restrictions of utilizing the GPS measurements: First, GPS measurements are not available in many environments adverse to signal reception such as jamming, or the positions blocked by many buildings, etc. Next, the GPS measurement outputs are not frequent enough for many applications such as vertical autopilot design. Finally, the GPS height tends to include larger errors than its horizontal position due to the satellite geometry. In this paper, a new height sensing system to cope with the above restrictions is proposed by combining the GPS height and air-data module (ADM) measurements.

ADM is a set of various sensors measuring the current conditions of the ambient atmosphere such as dynamic pressure, static pressure, temperature, etc. Since the height information is tightly related to the static pressure and the temperature, it can be obtained through some formula describing the relationship of the air data and height [Siouris, 1993]. The height information obtained by this way is frequently called 'baro-height' which is the well-known barometer output. This method is very robust to jamming situation because the ADM is a kind of self-contained sensor system. Moreover, since most ADM sensors are analog transducers, compared to the GPS, it is easy to achieve highly frequent measurements using ADM. These properties encourage the solution of the aforementioned inherited problems of GPS.

On the other hand, the errors of the baro-height tend to increase as the UAV moves away from the initial launching point. The reason is that, in general, barometers are initialized using the height, temperature, and pressure at the starting point of the vehicle. However, as time elapses and as the UAV moves to another place, the characteristics of the ambient air data are changed to produce large baro-height errors. To mitigate this problem, in this paper, a filter structure where the baro-height errors are estimated and compensated using the GPS measurements is proposed. For the baro-height error estimation, a Gaussian-approximation (GA) filter is derived based on the property that the baro-height errors are mainly composed of bias and scale factor errors. The estimated bias and scale factor errors are used to compensate the baro-height to produce highly frequent height estimates with a fairly good error bound. The detailed derivation and simulation results are included in the next chapters. For convenience, in this paper, the term 'baro-error' will be used for representing the errors of the baro-height computed using the ADM pressure measurements.

2. ALTITUDE ESTIMATOR DESIGN

2.1 Overview

The goal of this study is to construct a height estimator which can provide height estimates frequently enough for the application of autopilot design. In addition, its height output errors should be bounded by fusing the measurements of ADM and GPS. In order to meet the requirements, the height estimator shown in Fig.1 is proposed. The 'baro-height computation' block computes the current height called 'baro-height' using the ADM static pressure measurements. However, the baro-height is corrupted mainly by bias and scale factor errors, which are increasing with the elapse of time or with the movement of the vehicle [Whang *et. al.*, 2007]. The 'baro-error estimation' block in Fig.1 estimates these bias and scale factor errors by referencing the GPS heights and ADM temperature measurements. In our algorithm, the bias is estimated only with the GPS height measurements, but the scale factor error is estimated with both GPS heights and the ADM temperature measurements. Since GPS height output is not so frequent as the ADM output, the bias estimate is updated less frequently than the scale factor estimate.

The 'baro-error compensation filter' block in Fig.1 has two functions: (1) compensating the current baro-height based on the recent estimates of the bias and scale factor, and (2) predicting the 'next height' (one step ahead prediction) as well as filtering the compensated baro-heights. The predicted height or the 'a priori height estimate' signal in Fig.1 is used for cooking the ADM temperature measurement to produce the scale factor information.

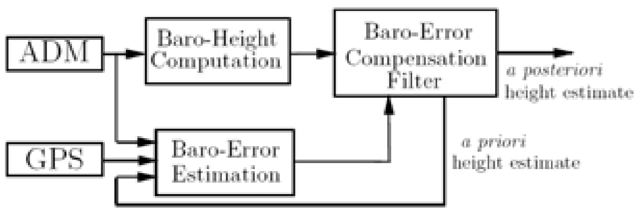

Fig.1. Structure of the Proposed Altitude Estimator

The final output height will be the filtered value of the compensated baro-heights. Since the proposed height estimator utilizes the ADM measurements and GPS measurements together, it is expected that the final height output can keep good error performance.

On the other hand, the baro-errors are expected to change very slowly compare to the actual height movement of the UAV because the baro-errors are originated from the ambient air data change which is very slow. The structure in Fig.1 isolates the slow baro-error dynamics from the fast actual height dynamics since the baro-error dynamics is considered only in the 'baro-error estimation' block. Consequently, the estimates of the baro-errors are expected to keep fair accuracy even when the GPS output rate is quite low. It means that the proposed height estimator can keep a fair performance in spite of a lot of adverse situations related to GPS availability.

In the next sections, the detailed description of each blocks in Fig.1 are provided.

2.2 Baro-Height Error Model and Measurement Model

The baro-height h_k^B is related to the ambient air data through the following equation [Siouris, 1993].

$$h_k^B = H_0 + \frac{T_0}{\Gamma}\left[\left(\frac{P_k}{P_0}\right)^{-\Gamma\frac{R}{g}} - 1\right] \tag{1}$$

In the equation, H_0, T_0, P_0 are the height, temperature, and pressure at the initial position of the UAV, respectively. In addition, R, Γ, g are the universal gas constant, lapse rate, and gravity constant, respectively. Therefore, once we set the parameters H_0, T_0, P_0 at the launch position of the UAV, the baro-height is obtained by evaluating (1) using the current pressure P_k sensed by ADM.

Perturbation of (1) results in the following equation showing the baro-errors mainly consist of the scale factor a_k and bias b_k [Whang *et. al.*, 2007].

$$h_k^B - h_k \approx a_k(h_k - H_0) + b_k\ , \tag{2}$$

$$a_k = \frac{\Delta T}{T_0} = \frac{T_0' - T_0}{T_0}\ , \tag{3}$$

$$b_k = \frac{RT_0}{g}\left(\frac{\Delta P}{P_0}\right) = \frac{RT_0}{g}\left(\frac{P_0' - P_0}{P_0}\right). \tag{4}$$

In the above equations, T_0' and P_0' are the temperature and the pressure in the height H_0 at current time k . If we regard

$$T = T_0 + \Gamma(h - H_0) \tag{5}$$

as the relation between heights and temperatures, a pseudo scale factor measurement λ_k can be constructed from the ADM temperature measurement since the scale factor depends only on the temperature changes as shown in (3).

$$\begin{aligned}\lambda_k &= \frac{T_k^{ADM} - \hat{\Gamma}(\hat{h}_{k|k-1} - H_0) - T_0}{T_0} \\ &\cong a_k + v_k^a\end{aligned} \tag{6}$$

In the equation, T_k^{ADM} , $\hat{\Gamma}$, and $\hat{h}_{k|k-1}$ are the ADM temperature measurement, the nominal lapse rate, and the *a priori* height estimate of the baro-error compensation filter, respectively. Besides, v_k^a is assumed to be a zero mean Gaussian random variable (RV) with the following variance.

$$Var\{v_k^a\} = \frac{Var\{T_k^{ADM}\} + \hat{\Gamma}^2 Var\{\hat{h}_{k|k-1}\} + \left(\hat{h}_{k|k-1} - H_0\right)^2 Var\{\hat{\Gamma}\}}{T_0} \tag{7}$$

In many cases, since the UAV takes off at the land or see, H_0 is negligible relative to h_k. Therefore, based on (2), the baro-height measurement model can be described by (8).

$$h_k^B = (1 + a_k)h_k + b_k + v_k^B \tag{8}$$

In (8), h_k, h_k^B, and v_k^B are the actual height, barometer height measurement, and baro-height random error, respectively. And v_k^B is assumed to be a zero mean white Gaussian RV with its variance of R_k^B.

Let the GPS height measurement model be

$$h_k^{GPS} = h_k + v_k^{GPS}. \tag{9}$$

Similar to the barometer case, v_k^{GPS} is assumed to be a zero mean white Gaussian RV with its variance of R_k^{GPS}, too. For direct consideration of the baro-errors, the difference of (8) and (9) will be handled as a measurement in the derivation of the baro-error estimation filter. In detail, through some approximations, the measurement will be

$$\begin{aligned} z_k &= h_k^B - h_k^{GPS} \\ &\cong h_k^{GPS} a_k + b_k + v_k \end{aligned}. \tag{10}$$

In (10), under the assumption of small a_k, v_k is modeled by a zero mean white Gaussian RV with its variance of $R_k = R_k^B + R_k^{GPS}$.

In summary, now we have the two kinds of the measurements of λ_k and z_k whose models are given by (6) and (10). Note that λ_k is available at the rate of ADM measurements while z_k is at the rate of GPS measurements.

2.3 Baro-Error Estimation

As mentioned in the previous section, baro-errors are mainly made up of the bias and the scale factor errors which originated from the change of ambient air data. Based on this fact, the bias and scale factor errors can be modeled using random walks as follows:

$$a_{k+1} = a_k + w_k^a \tag{11}$$

$$b_{k+1} = b_k + w_k^b \tag{12}$$

In the above equations, the process noises of scale factor and bias of w_k^a and w_k^b are assumed to be zero mean white Gaussian RV with their variances of Q_k^a and Q_k^b.

Let the filter state be the scale factor 'a_k' and bias error 'b_k'. Then, the baro-error estimation problem becomes the evaluation of the probability density function (pdf) of the state. It is well known that Kalman filter (KF) is the pdf evaluation process for the linear Gauss Markov systems [Maybeck, 1979]. And our problem seems to be the very estimation problem since we have linear system model of (11)-(12) and linear measurement model of (6) and (10). However, the conventional KF can not be an adequate solution of the problem since (10) includes the uncertain parameter of h_k^{GPS}. Due to the reason, in order to tackle the problem, we apply the Gaussian-Approximation (GA) filter technique. The concept of this technique is to approximate the pdf of the state with a Gaussian pdf at the end of each filtering stage. So, the standing assumption will be that the pdf of the states is Gaussian at each sampling time.

The proposed baro-error estimator consists of three blocks; system propagation, λ_k-update, z_k-update. Note that λ_k is more frequent than z_k, since ADM measurements are provided more frequently than GPS height. In order to cope with the different measurement rate problem, at each ADM sampling time, system propagation and λ_k-update are carried out. But z_k-update is executed only when the GPS height measurement is received.

By the standing assumption of GA filter, we can start with the following Gaussian pdf at k.

$$\Pr\{a_k \mid Z^k\} \sim N\{a_k - \hat{a}_{k|k}; P_{k|k}^a\} \tag{13}$$

$$\Pr\{b_k \mid Z^k\} \sim N\{b_k - \hat{b}_{k|k}; P_{k|k}^b\} \tag{14}$$

In the above equations, $N\{x - m; P\}$ is the pdf of the Gaussian random vector with mean m and variance P. And Z^k stands for the set of initial state and the accumulated measurements of λ_i and z_i from $i = 1$ to k.

The 'system propagation' is to evaluate *a priori* pdf of the state. The evaluation can be easily accomplished using the system model of (11) and (12) since sum of two Gaussian RVs is Gaussian [Maybeck, 1979]. And the results are as follows:

$$\Pr\{a_{k+1} \mid Z^k\} \sim N\{a_{k+1} - \hat{a}_{k+1|k}; P_{k+1|k}^a\}, \tag{15}$$

$$\Pr\{b_{k+1} \mid Z^k\} \sim N\{b_{k+1} - \hat{b}_{k+1|k}; P_{k+1|k}^b\}. \tag{16}$$

In the above equations,

$$\hat{a}_{k+1|k} = \hat{a}_{k|k},\ P_{k+1|k}^a = P_{k|k}^a + Q_k^a, \tag{17}$$

$$\hat{b}_{k+1|k} = \hat{b}_{k|k},\ P_{k+1|k}^b = P_{k|k}^b + Q_k^a. \tag{18}$$

The 'λ_k-update' equation can also be obtained by the conventional KF since λ_{k+1} satisfies the assumptions of KF. Consequently,

$$\Pr\{a_{k+1} \mid Z^k, \lambda_{k+1}\} \sim N\{a_{k+1} - \hat{a}_{k+1|k}^\lambda; P_{k+1|k}^\lambda\}. \tag{19}$$

In (19),

$$\hat{a}_{k+1|k}^\lambda = \hat{a}_{k+1|k} + K_{k+1}^\lambda(\lambda_{k+1} - \hat{a}_{k+1|k}), \tag{20}$$

$$P_{k+1}^{\lambda} = \left[1 - K_{k+1}^{\lambda}\right] P_{k+1|k}^{a}, \tag{21}$$

$$K_{k+1}^{\lambda} = P_{k+1|k}^{a}\left[P_{k+1|k}^{a} + Var\left\{v_{k+1}^{a}\right\}\right]^{-1}. \tag{22}$$

Whenever the GPS measurements are received, the 'z_k-update' is additionally carried out to obtain the *a posteriori* pdf of $\Pr\{a_{k+1} \mid Z^{k+1}\} = \Pr\{a_{k+1} \mid Z^k, \lambda_{k+1}, z_{k+1}\}$ and $\Pr\{b_{k+1} \mid Z^{k+1}\}$ $= \Pr\{b_{k+1} \mid Z^k, \lambda_{k+1}, z_{k+1}\}$. The evaluation of the probability begins with the following definitions:

$$\alpha_{k+1}^{(i)} = \Pr\left\{a_{k+1} = a^{(i)} \mid Z^{k+1}\right\}, \quad z_{k+1}^{a} = \frac{1}{h_{k+1}^{GPS}}\left(h_{k+1}^{B} - h_{k+1}^{GPS} - \hat{b}_{k+1|k}\right),$$

and $S_{k+1}^{a} = \frac{1}{\left(h_{k+1}^{GPS}\right)^2}\left(P_{k+1|k}^{b} + R_{k+1}\right)$.

Then, the followings are obtained by some computations based on the Bayesian rule.

$$\begin{aligned}
\alpha_{k+1}^{(i)} &= \frac{1}{c}\Pr\left\{z_{k+1} \mid a_{k+1} = a^{(i)}, Z^k, \lambda_{k+1}\right\}\Pr\left\{a_{k+1} = a^{(i)} \mid Z^k, \lambda_{k+1}\right\} \\
&\propto N\left\{z_{k+1}^{a} - a^{(i)}; S_{k+1}^{a}\right\} N\left\{a^{(i)} - \hat{a}_{k+1|k}^{\lambda}; P_{k+1}^{\lambda}\right\} \\
&\propto \exp\left\{-\frac{1}{2}\left[\frac{1}{S_{k+1}^{a}}\left(z_{k+1}^{a} - a^{(i)}\right)^2 + \frac{1}{P_{k+1}^{\lambda}}\left(a^{(i)} - \hat{a}_{k+1|k}^{\lambda}\right)^2\right]\right\} \\
&\propto N\left\{a^{(i)} - \frac{P_{k+1}^{\lambda} z_{k+1}^{a} + S_{k+1}^{a}\hat{a}_{k+1|k}^{\lambda}}{P_{k+1}^{\lambda} + S_{k+1}^{a}}; \frac{P_{k+1}^{\lambda} S_{k+1}^{a}}{P_{k+1}^{\lambda} + S_{k+1}^{a}}\right\}
\end{aligned} \tag{23}$$

It means

$$\Pr\left\{a_{k+1} \mid Z^{k+1}\right\} \sim N\left\{a_{k+1} - \hat{a}_{k+1|k+1}; P_{k+1|k+1}^{a}\right\} \tag{24}$$

where

$$\begin{aligned}
\hat{a}_{k+1|k+1} &= E_i\left\{a^{(i)} \mid Z^{k+1}\right\} \\
&= \frac{S_{k+1}^{a}}{P_{k+1}^{\lambda} + S_{k+1}^{a}}\hat{a}_{k+1|k}^{\lambda} + \frac{P_{k+1}^{\lambda}}{P_{k+1}^{\lambda} + S_{k+1}^{a}} z_{k+1}^{a}, \\
&= \hat{a}_{k+1|k}^{\lambda} + \frac{P_{k+1}^{\lambda}}{P_{k+1}^{\lambda} + S_{k+1}^{a}}\left(z_{k+1}^{a} - \hat{a}_{k+1|k}^{\lambda}\right)
\end{aligned} \tag{25}$$

$$P_{k+1|k+1}^{a} = \frac{P_{k+1}^{\lambda} S_{k+1}^{a}}{P_{k+1}^{\lambda} + S_{k+1}^{a}} = \left[1 - \frac{P_{k+1}^{\lambda}}{P_{k+1}^{\lambda} + S_{k+1}^{a}}\right] P_{k+1}^{\lambda}. \tag{26}$$

As a result, the 'z_k-update' equations for the scale factor 'a_{k+1}' are (25) and (26) which can be interpreted as a kind of KF measurement update equations for the pseudo scale factor measurement z_{k+1}^{a}.

Before evaluating the *a posteriori* pdf for the bias, let us define the $\left\{a_{k+1} = a^{(i)}\right\}$-conditioned bias estimate by the mean bias computed under the assumption of $\left\{a_{k+1} = a^{(i)}\right\}$. The estimate can easily be obtained by the following KF equations with the measurement of $z_{k+1} - h_{k+1}^{GPS} a^{(i)}$.

$$\begin{aligned}
\hat{b}_{k+1|k+1}^{(i)} &= E\left\{b_{k+1|k+1} \mid a_{k+1} = a^{(i)}, Z^{k+1}\right\} \\
&= \hat{b}_{k+1|k} + K_{k+1}^{b(i)}\left(z_{k+1} - h_{k+1}^{GPS} a^{(i)} - \hat{b}_{k+1|k}\right)
\end{aligned} \tag{27}$$

$$P_{k+1|k+1}^{b(i)} = \left[1 - K_{k+1}^{b(i)}\right] P_{k+1|k}^{b}, \tag{28}$$

$$K_{k+1}^{b(i)} = P_{k+1|k}^{b}\left[P_{k+1|k}^{b} + R_{k+1}\right]^{-1}. \tag{29}$$

Note that $P_{k+1|k+1}^{b(i)}$ and $K_{k+1}^{b(i)}$ are independent of $a^{(i)}$ although their notation includes the symbol of '(i)'. Since now we have every $\left\{a_{k+1} = a^{(i)}\right\}$-conditioned bias estimate, the *a posteriori* pdf for the bias can be evaluated as the limit of Gaussian mixture pdf [Bar-Shalom, 1988]. Hence the mean and variance of the pdf will be (30) and (31).

$$\begin{aligned}
\hat{b}_{k+1|k+1} &= \sum_i \hat{b}_{k+1|k+1}^{(i)}\alpha_{k+1}^{(i)} \\
&= \hat{b}_{k+1|k} + K_{k+1}^{b(i)}\left(\sum_i\left(z_{k+1} - h_{k+1}^{GPS} a^{(i)}\right)\alpha_{k+1}^{(i)} - \hat{b}_{k+1|k}\right) \\
&= \hat{b}_{k+1|k} + K_{k+1}^{b(i)}\left(z_{k+1}^{b} - \hat{b}_{k+1|k}\right)
\end{aligned} \tag{30}$$

In (30), $z_{k+1}^{b} = z_{k+1} - h_{k+1}^{GPS}\hat{a}_{k+1|k+1}$. Since $P_{k+1|k+1}^{b(i)}$ and $K_{k+1}^{b(i)}$ are independent of $a^{(i)}$, the variance of the bias will be given by (31).

$$\begin{aligned}
P_{k+1|k+1}^{b} &= \left[1 - K_{k+1}^{b(i)}\right] P_{k+1|k}^{b} + \sum_i\left(\hat{b}_{k+1|k+1}^{(i)} - \hat{b}_{k+1|k+1}\right)^2\alpha_{k+1}^{(i)} \\
&= \left[1 - K_{k+1}^{b(i)}\right] P_{k+1|k}^{b} + \left(K_{k+1}^{b(i)} h_{k+1}^{GPS}\right)^2\sum_i\left(\hat{a}_{k+1|k+1}^{(i)} - \hat{a}_{k+1|k+1}\right)^2\alpha_{k+1}^{(i)} \\
&= \left[1 - K_{k+1}^{b(i)}\right] P_{k+1|k}^{b} + \left(K_{k+1}^{b(i)} h_{k+1}^{GPS}\right)^2 P_{k+1|k+1}^{a}
\end{aligned} \tag{31}$$

As a result, the 'z_k-update' equations for the bias 'b_{k+1}' will be (29), (30), and (31).

As mentioned before, according to the availability of the GPS height measurement, one batch of the baro-error estimation process is selected to be either '(system propagation) + (λ_k-update)' or '(system propagation) + (λ_k-update) + (z_k-update)' at each filtering stage. At the end of each stage the pdfs of 'a_k' and 'b_k' are approximated to the Gaussian pdf with their final means and variances - viz. the former batch produces the Gaussian pdf with the parameters in (18) and (19), but the latter batch does with (24), (30), and (31).

2.4 Baro-Error Compensation Filter

The baro-error compensation filter consists of two parts – correcting the baro-heights and filtering the corrected heights. The baro-height correction is performed using the last estimates of the scale factor and bias as follows:

$$h_{k+1}^{c} = \frac{h_{k+1}^{B} - \hat{b}_{last}}{1 + \hat{a}_{last}}. \tag{32}$$

In (32), $\hat{a}_{last}$ and $\hat{b}_{last}$ are the last estimate of the scale factor and bias. As stated in the last paragraph in sec. 2.3, they can be either { $\hat{a}^{\lambda}_{k+1|k}, \hat{b}_{k+1|k}$ } or { $\hat{a}_{k+1|k+1}, \hat{b}_{k+1|k+1}$ } depending on the availability of GPS heights at current time.

Even though the bias and scale factor errors are compensated, the corrected height h^c_{k+1} still has random errors as the baro-height has random errors shown in (8). Moreover, the scale factor measurement cooking process of (6) requires the one-step-ahead prediction of the current height. In order to solve these two problems, the corrected height h^c_k is filtered using a simple alpha-beta filter is used. It is easily designed by applying the KF to the following simple signal model.

$$x_{k+1} = F_k x_k + G_k w^h_k \tag{33}$$

$$y_k = H_k x_k + v^h_k \tag{34}$$

In the above equations, $x_k = \begin{bmatrix} h_k \\ \dot{h}_k \end{bmatrix}$, $F_k = \begin{bmatrix} 1 & \Delta t^B \\ 0 & 1 - \frac{1}{\tau}\Delta t^B \end{bmatrix}$, $G_k = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$, $y_k = h^c_k$, and $H_k = [1 \quad 0]$. In addition, w^h_k and v^h_k are assumed to be mutually uncorrelated zero mean white Gaussian random variables with their covariances of Q^h_k and R^h_k. Moreover, through some manipulations of (32), R^h_k becomes $R^h_k = \dfrac{(h^c_k)^2 P^a_{last} + P^b_{last} + R^B_k}{(1+\hat{a}_{last})^2}$.

The *a priori* estimate and *a posteriori* estimate of the alpha-beta KF will be the very '*a priori* height estimate' and '*a posteriori* height estimate' in Fig.1. And eventually they are the final output of the 'baro-error compensation filter'.

3. SIMULATION

In this chapter, the performance of the proposed altitude estimator is investigated by a realistic simulation. Simulation conditions are as follows:

- No. of Monte Carlo simulation trials = 50

- ADM meas. period (Δt^B) = 0.2 sec

- GPS meas. period = 1.0 sec

- At every 10 sec, lapse rate changes randomly with the s.d. of $0.003°C/km$ around its nominal value of $-0.0065°C/km$.

- Meas. error covariances: $R^{GPS}_k = 70^2[m^2]$, $R^B_k = 5^2[m^2]$, $R^{Temperture}_k = 1.5^2[\deg^2]$

- Air data process noise covariances:

$Q^a_k = 2\times10^{-5}$, $Q^b_k = 400$

- Baro-error estimation GA filter parameters:

$P^a_{0|0} = 0.2^2$, $P^b_{0|0} = 20^2$

- Baro-error compensation filter parameters:

$Q^h_k = 39.69$, $P_{0|0} = diag\{100,144\}$, $\tau = 100$.

- The height trajectory shown in Fig.2 is used in the simulation.

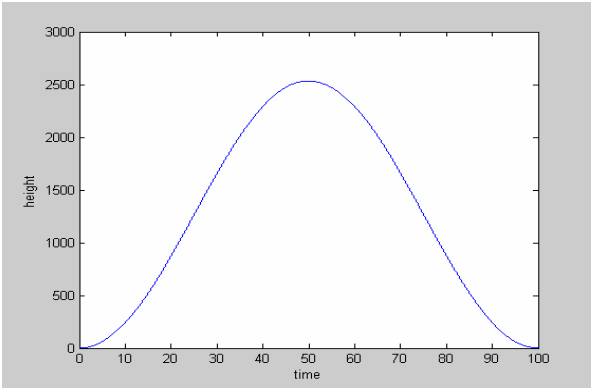

Fig.2. Height Trajectories used in the Simulation

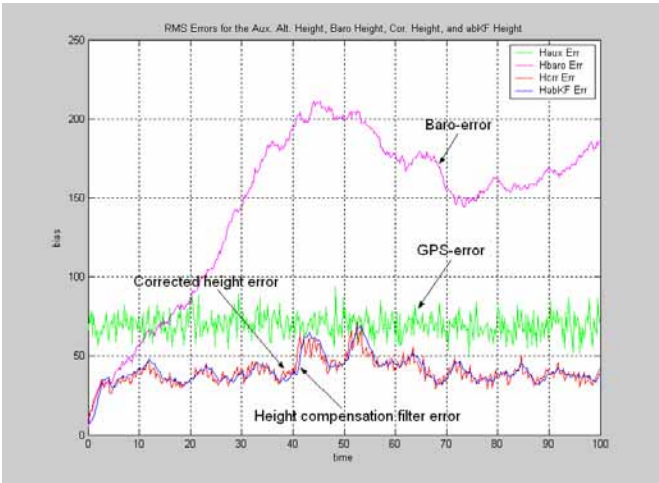

Fig.3. RMS Errors for Comparison

Fig.3. shows the root mean squares (RMS) error trajectories of baro-height errors, GPS-height errors, compensated height(h^c_k) errors, and final height output errors of the proposed altitude estimator. As we can see in the figure, the proposed altitude estimator works so well that it can suppress the height estimation errors under the GPS error level. It implies that the proposed altitude estimator effectively fuses the information of the measurements of ADM and GPS to produce accurate height estimates.

4. CONCLUSIONS

In this paper, a new altitude estimator which is simple but accurate is proposed. The estimator is constructed based on the baro-error estimation and compensation structure. Beginning with the fact that the baro-errors mainly consist of bais and scale factor errors, a new filter to estimate the bias and scale factor using the GPS-heights and ADM temperature measurements is derived under the concept of GA filtering. Simulation result shows that the proposed filter works very well. It implies the possibility to construct accurate height measurement systems for small UAVs using only ADM and GPS without expensive INS.

REFERENCES

Siouris, G.M., *Aerospace Avionics Systems*, Academic Press, 1993.

Whang, I-H and Ra W-S, "Zero-Scan-Back Reference Height Generation Filter," Information and Control Symposium, KIEE & IEEK, Jeon-Ju, April, 2007

Maybeck, P.S., *Stochastic Models, Estimation, and Control*, Vol. 1, Academic Press, 1979

Bar-Shalom, Y. and Fortmann, T.E., *Tracking and Data Association,* Academic Press, Inc., 1988.