Development of an Integrated Attitude Determination System for Small Unmanned Aerial Vehicles patterned after Simple Neural Networks

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Abstract - *The present study was undertaken in order to arrive at an alternative and computationally friendly solution to the problem of attitude determination for a small unmanned aerial vehicle. The effort consisted in reviewing several accounts of attitude determination strategies as well as the nature and functions of neural networks. Experiments were carried out to test conceptual approaches and determine pertinent parameters of the proposed system. At the end of the study, an algorithm that fuses information from the global navigation satellite systems sensor, accelerometer, gyroscope and magnetometer to determine the attitude of a small unmanned aerial vehicle, using the principle of operation of a simple neural network was realized. The performance of the proposed algorithm was evaluated by comparing its output with those of a traditional method.*

Key Words: Unmanned aerial vehicle, attitude determination, inertial measurement unit, neural network, global navigation satellite system

1. INTRODUCTION

Unmanned aerial vehicles (UAVs) have proven to be very useful in several scenarios including surveying and mapping, package delivery, surveillance, precision agriculture, recreation, and military uses such as intelligence gathering, target acquisition and warhead delivery [1]. Small UAVs have a maximum weight of 25 kg [2], and usually come with micro-electro-mechanical system (MEMS) sensors, usually accelerometers, gyroscopes and magnetometers, in addition to a global navigation satellite system (GNSS) sensor, that provide a low-cost, small form-factor sensor solution [3]. This work seeks to take advantage of all of the data provided by these sensors to determine the attitude of the aircraft. Knowledge of vehicle attitude is necessary because a change in flight path is accomplished by a change in attitude [4, 5]. We begin by examining attitude solutions from the individual sensors.

2. INDIVIDUAL SENSOR ATTITUDE SOLUTIONS

2.1 Gyroscopes

The rate gyroscopes onboard a UAV may be used to determine its attitude [6]. In order to do this, it is necessary to propagate the attitude in time, and a suitable representation of the attitude is required. It is possible to use a rotation matrix or quaternion, but the latter is preferred because it avoids singularities at pitch angles of $\pm 90^0$, has better numerical stability, and higher efficiency [7].

The differential equation which relates the quaternion attitude rates to angular velocity is given by [8] as,

$$\dot{q} = \begin{bmatrix} \dot{q_0} \\ \dot{q_1} \\ \dot{q_2} \\ \dot{q_3} \end{bmatrix} = \frac{1}{2}\begin{bmatrix} 0 & -p & -q & -r \\ p & 0 & r & -q \\ q & -r & 0 & p \\ r & q & -p & 0 \end{bmatrix}\begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix} \equiv \frac{1}{2}\Omega q \quad (1)$$

where p, q and r are the angular velocities measured by the gyroscope, and q_0, q_1, q_2 and q_3 are the components of the attitude quaternion, q. Integrating Equation 1 provides the attitude at any time, given its initial value.

2.2 Accelerometers

Accelerometers may be used as inclinometers to determine pitch and roll [9, 10]; this is based on sensing earth's gravity [11]. For the UAV in motion, the acceleration of the platform must be isolated from the accelerometer outputs before they can be used to compute attitude [12]. Platform acceleration may be obtained by differentiating twice, the position measurements from a GNSS sensor [13].

The following equation holds for navigation over the surface of the earth [14]:

$$\dot{V} = f - 2\omega_{ie} \times V + g \quad (2)$$

where,

V is the velocity of the vehicle, f is the specific force vector, ω_{ie} is the earth's rotation rate and g is the acceleration due to gravity, all expressed in the earth frame.

We obtain V and $\dot{V}$ from the GNSS measurements; ω_{ie} is a known constant; and g is calculated using the position of the vehicle (also obtained from the GNSS sensor). f is measured by the accelerometers (in body coordinates), and the quaternion, $q_{e/n}$, performs transformation of f from the navigation frame to the earth frame. It remains therefore to determine the quaternion, $q_{n/b}$, that performs the rotation of f from body coordinates to navigation coordinates.

2.3 Magnetometers

Magnetometers exploit the earth's magnetic field to determine the attitude of a vehicle. Knowing the magnetic field components in the local geographic frame – as provided by a model such as the World Magnetic Model [15], together with the sensor measurements (in the body frame), the quaternion that performs the transformation between the two frames may be determined, and hence the heading.

3. INTEGRATED SYSTEM MODEL

3.1 Architecture

The integrated attitude determination system is modelled after a simple neural network [16, 17], as illustrated in Figure 1.

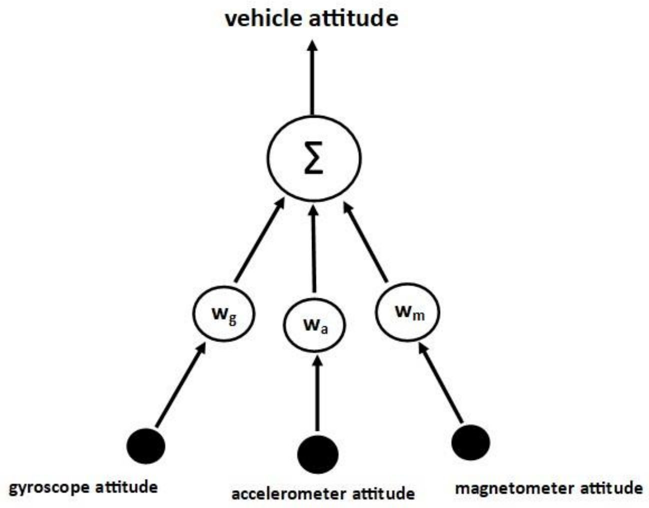

Fig -1: System model for integrated attitude determination

The attitude of the vehicle is derived from the weighted sum of the individual inputs from the gyroscope, accelerometer and magnetometer.

Thus,

$$\theta = w_g \cdot \theta_g + w_a \cdot \theta_a + w_m \cdot \theta_m \qquad (3)$$

where θ represents attitude, and the subscripts g, a and m, stand for gyroscope, accelerometer and magnetometer, respectively.

It now remains to determine the weights. Two sources that contribute to the weight may be identified; they are:

1. The measurement uncertainty associated with the particular sensor
2. The deviation of the particular sensor attitude solution from the mean of all sensor values

The total weight is computed as,

$$w = \alpha \cdot \sqrt{{w_1}^2 + {w_2}^2} \qquad (4)$$

where, w_1 is the weight due to sensor error, w_2 is the weight due to deviation from the mean and α is a weighting coefficient that ensures that a smaller weight is chosen for a large error value, and vice versa, determined by minimizing the least-squares error between the weighted attitude solution and that provided by a traditional algorithm.

3.2 Weight due to sensor error

It seems rational to control the influence of the output of a particular sensor on the overall attitude by examining the value of its error term. The weight due to sensor error is given by,

$$w_1 = \delta_1 \qquad (5)$$

where δ_1 is a normalized error value.

The approach is to compute the root-mean-square value of the error spectrum of the sensor. This may be accomplished in the following way [18].

Given the sensor output in the absence of any input,

$$\omega = {2\pi k}/{T} \qquad (6)$$

where k is the sample number (k = 1, 2, ..., N), and T is the length of the time ensembles, given by $T = N * \Delta t$, where N is the number of samples and Δt is the sample time [19];

$$|H(j\omega)| = \sqrt{|\Gamma(j\omega)|} \qquad (7)$$

where, $\Gamma(j\omega)$ is the Fourier transform of the output, computed using any one of the algorithms provided by [20 - 23];

1. Beginning at the first data point $(\omega_i, |H|_i)$, and considering also the consecutive point $(\omega_{i+1}, |H|_{i+1})$, the area under the segment joining the two points is calculated as,

$$a_i = \frac{1}{2}\log\left(\frac{\omega_{i+1}}{\omega_i}\right) \cdot \log(|H|_{i+1} \cdot |H|_i) \quad (8)$$

2. The RMS value is then calculated as,

$$L = \sqrt{\sum_{i=1}^{m} a_i}, \quad (9)$$

where m is the total number of segments

The RMS error is used as a constant sensor measurement value to derive an attitude estimate, $\delta\theta_i$ that is propagated in time.

δ_1 is then calculated from,

$$\delta_{1,i} = \frac{\delta\theta_i}{|\delta\theta_i|} \quad (10)$$

where *i* is the particular sensor (accelerometer, gyroscope or magnetometer).

3.3 Weight due to deviation from mean attitude

Turning to the second factor that contributes to the weights, the approach used by [24] is adapted. The sensor values are used to derive individual attitude estimates. The mean of these estimates is then determined, as well as the corresponding deviation of each sensor from this value. The weight due to deviation from the mean is given by,

$$w_2 = \delta_2 \quad (11)$$

where,

δ_2 is a normalized error value calculated from,

$$\delta_{2,i} = \frac{\delta\psi_i}{|\delta\psi_i|} \quad (12)$$

and $\delta\psi$ is the deviation of the particular sensor attitude solution from the mean.

4. EVALUATION

A commercial UAV with an onboard flight controller was flown, and a log taken of its flight parameters; these included the time, GPS coordinates, accelerometer, magnetometer and gyroscope readings, and components of the attitude quaternion as computed by the flight controller's Attitude and Heading Reference System (AHRS). About a minute's worth of stationary data was also obtained, from which the error properties of the inertial sensors were determined. The proposed attitude determination algorithm was then applied and its outputs compared with those of the AHRS. The results of the experiment are shown in Figures 2 to 4.

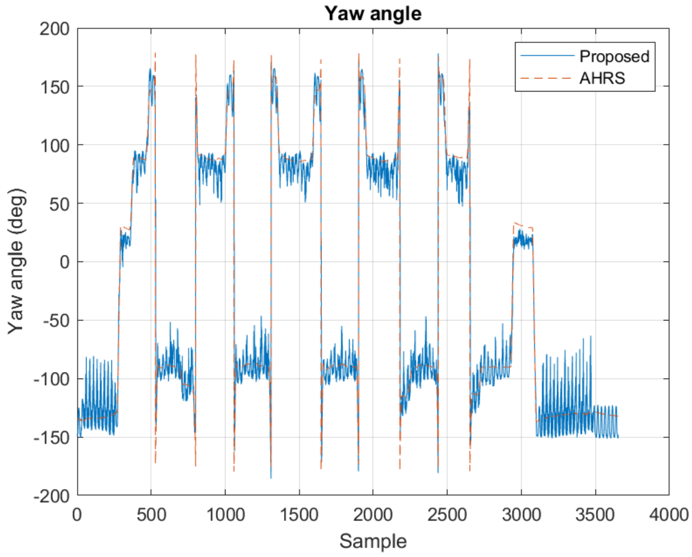

Fig -2: Yaw angle from proposed algorithm compared with traditional solution

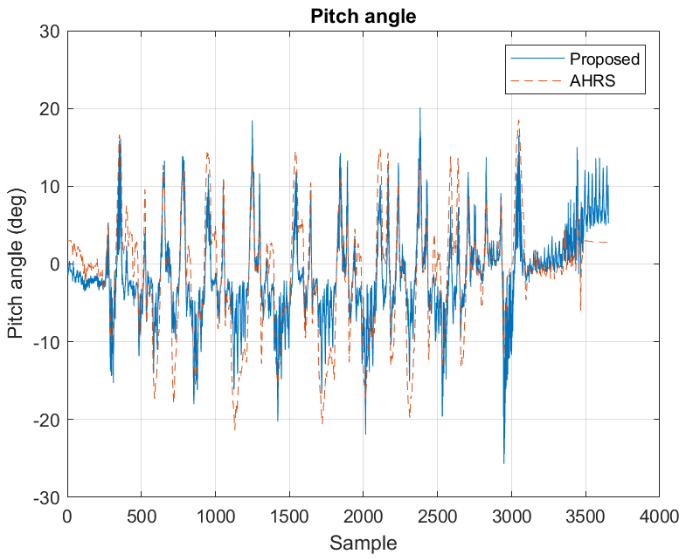

Fig -3: Pitch angle from proposed algorithm compared with traditional solution

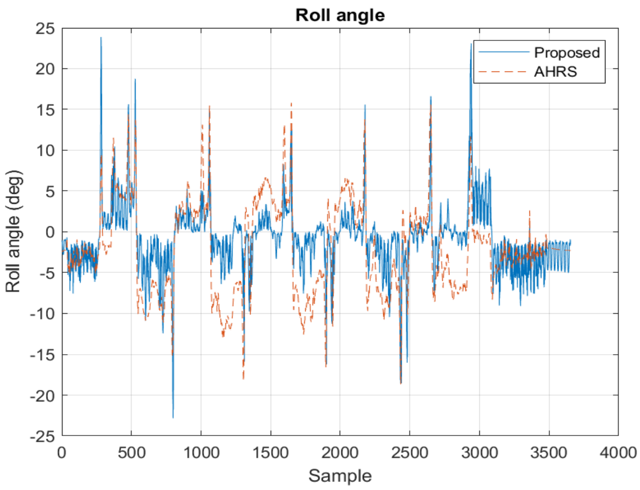

Fig -4: Roll angle from proposed algorithm compared with traditional solution

It can be seen that there is very good agreement between the AHRS attitude solution and the proposed one. The largest root mean square error was 23.1^0, recorded along the yaw channel. This large error is likely due to the abrupt changes in the UAVs heading, as derived from its flight path. Error values for the pitch and roll channels were 4.9^0 and 4.2^0 respectively, confirming good agreement between the two algorithms.

5. CONCLUSION

The study set out to develop an alternative method for computing the attitude of a small UAV, taking advantage of all sensors onboard. In the end, an algorithm that fuses the attitude solution obtained from the individual sensors in a configuration similar to a simple neural network, using weights derived from sensor noise and deviation from mean attitude, and requiring very little processing power was developed.

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