Robust Sensor Fusion for State Estimation on Agile Electric UAVs

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Abstract—There has been a rapid increase in the use of unmanned aerial vehicles (UAVs). On UAVs, autopilots are fundamental components that use a variety of sensors to estimate vehicle’s state and perform actuation, ultimately allowing to perform the assigned tasks. Modern UAVs are often being powered by electric motors which provide a number of advantages over internal combustion engines, in terms of weight, actuation delay, vibrations and so on. Unfortunately, electric propulsion systems have the inherent disadvantage of producing large varying magnetic fields. Such fields heavily interfere with magnetometer units, creating large errors in their readings and ultimately leading to erroneous estimation of aircraft attitude and position.

In this work we (a) investigate the magnitude of side effects caused by electric motor induced magnetic fields on accelerometers, gyro, and magnetometers. In addition, we (b) propose a sensor fusion algorithm to correct the erroneous attitude determination using a lightweight integration method relying on magnetic-insensitive inertial sensors. We validate the correctness of our algorithm using real flight data from an agile maneuver achieving an accuracy of greater than 99.7%.

I. INTRODUCTION

There has been a rapid increase in unmanned aerial vehicle (UAV) development and use, more specifically, the number of low-cost, small- to mid-size size UAVs has exploded in recent years. These vehicles feature autopilot systems that monitor the state of the aircraft and produce actuation commands. For UAVs to successfully perform their assigned tasks, a robust and accurate autopilot system is indispensable. Autopilot systems use a variety of sensors to ascertain the aircraft’s state and faulty reading can lead to vehicle loss.

More and more often, small- to mid-size fixed-wing UAVs are being powered by electric motors rather than the more historically traditional internal combustion engines found on larger vehicles. Electric motor systems provide a handful of advantages over internal combustion engines such as: creating lower vibration, which decreases the noise recorded by intertial sensors and the rate of airframe fatigue thereby increasing the aircraft’s lifetime; providing repeatable performance and not needing to be tuned to the specific atmospheric conditions; and having constant system weight and distribution, thereby not altering the aircraft’s inertial properties as a result of fuel burn. However, electric propulsion systems have the inherent disadvantage of producing large varying magnetic fields.

The problem with these induced magnetic fields is that they interfere with magnetometer measurements. Magnetometer readings are a vital component in extended-Kalman filter (EKF) estimation of aircraft attitude and position. The contribution of this work is twofold. First, we thoroughly investigate the magnitude of negative effects caused by electric motor induced magnetic fields. Specifically, we evaluate the amount of interference that is introduced into the measurements retrieved from accelerometers, gyro, and magnetometers, as well as the extend to which the EKF produces erroneous state estimation. Second, we build upon the observation that accelerometers and gyro are insensitive to magnetic filed variations. Thus, we propose a sensor fusion algorithm to correct the erroneous attitude determination using a lightweight integration method. The validity of our algorithm is demonstrated using real flight data.

We envision that the proposed algorithm can be stably integrated in commercial and custom autopilots to support the correct determination of UAV attitude under those conditions where bare sensor measurements are not reliable (e.g. acrobatic flight). We show that since our data acquisition is performed at twice as fast as the actuation frequency, at 100 Hz, our algorithm can be used on-line.

The rest of the paper is organized as follows. Section II, provides background about sensor fusion and data acquisition requirements along with a brief review of work relating to that topic. In Section III, information about electric motor operation and problems relating to magnetic fields created by their use will be given. After that, a solution strategy will be discussed in Section IV. Then in Section V, a methodology description of the sensor-fusion algorithm used combat the magnetic fields will be given. Section VI, will provide evaluation of our sensor-fusion algorithm solution using real flight data. Finally, the paper concludes in Section VII.

II. BACKGROUND AND RELATED WORK

As previously mentioned, small- and mid-sized UAVs are increasingly being designed to operate with electric motors. Such solutions, if compared to gasoline engines, provides a number of advantages that include: less vibrations to the body; less maintenance; more repeatable performances over time and atmospheric conditions; less actuation delay for precise control purposes. However, as we will thoroughly study in Section III, electric motors introduce variable and strong magnetic fields in proximity of the on-board avionic units. In most of the cases, electric motors can result in far stronger magnetic fields than of Earth’s magnetic field, thereby inducing faulty measurements to the magnetometers. Since such measurements are directly used by the autopilot for attitude calculation, it follows that
the error propagation can lead to severe miscalculations and crashes if not correctly accounted.

Little research as been conducted in this direction, and a common denominator in the available related work is that ad-hoc approaches are commonly used. As a result, the negative effects caused by electric motor induced magnetic fields to UAV state measurement and control can be sparsely found in literature. Magnetic field offsets caused by the UAV’s motor(s) are often acknowledged to be one of the reasons for improper heading estimates [1, 2, 3, 4, 5]. Of these, several papers discussed a variety of methods to correct motor induced magnetic readings. The proposed methods involve corrections based on constant soft and hard iron offsets [3, 4]; measured offset generated look-up tables [4]; and state-based perturbation estimations [5].

The work in [6] presents some similarities with our approach. If fact, while discussing methods to calibrate inertial and magnetic sensors, it provides the intuition that position and orientation information can be found through a double integration process. However, the exact methodology is neither detailed nor experimented.

What sets our work apart is that we present a more general solution to the problem of reconstructing an accurate view of the aircraft attitude. Our solution entirely relies on sensors (gyroscopes and accelerometers) that are not affected by the motor-induced magnetic field. Moreover, the solution results usable for on-line operations if the UAV is equipped with an on-board data acquisition unit which is able to sample at a sustained 100 Hz frequency.

In [7] we proposed a software/hardware architecture for data acquisition that is able to fulfill the aforementioned requirement and that enables the on-line deployment of the proposed algorithm. Such a unit can be built from commercial components and is depicted in Figure 1. A detailed overview of its features and capabilities is provided in Table I.

As is detailed in Section V, each integration step performed by our sensor-fusion algorithm produces an output for the aircraft’s state at that given instant of time. Ideally, to produce the output at the current instant of time, the latest sensor reading should be used. However an optimization can be exploited to reduce the latency of the algorithm: since the intrinsic dynamics of the system evolve at 50 Hz, whereby control is performed at that rate, and given that our acquisition unit can sample at a double frequency, it follows that - for state estimation purposes - the deltas in the measurements of consecutive samples are negligible. As a result, the algorithm to produce the sensed attitude at the current time can be run on the data sample acquired immediately in advance.

## III. MOTOR OPERATION AND INTERFERENCE STUDY

Most small- to mid-size fixed-wing UAVs operated today are propelled using electric motors. Electric motors have a wide range of advantages however have the inherent disadvantage of creating varying magnetic fields. At a high level, an electric motor is a device that converts electrical energy into mechanical energy. Electric motors operate by using the interaction between the motor’s magnetic field and winding currents to generate force within the motor and therefore create a torque, which causes rotation.

Most UAVs that are powered by electric propulsion system use brushless DC (BLDC) motors for propulsion. BLDC motors have two primary parts: the rotor, which is the rotating part made up of permanent magnets, and the stator, which is the stationary part made up of windings. There are two types of BLDC motor designs: outer rotor and inner rotor. In an outer rotor design, the stator is located in the core of the motor and the rotor surrounds it and is affixed to the housing which rotates. In an inner rotor design, the stator surrounds the rotor and the stator is affixed to the motor’s housing which remains stationary. In both cases, the stator is made up of independent coils that are located next to each other in a circular pattern and can be activated in evenly spaced sets (e.g. coils 1, 3, and 5 are turned off while 2, 4, 6 are turned on).
When the motor operates, the rotor magnets are rotated in steps from one stator coil set to the next by commutating the currents between adjacent stator coils. Commutating the current turns off the magnetic field in one set of coils and turns the magnetic field in another set which causes the permanent magnet to be attracted and thereby causes the motor to rotate that step. This process is repeated in a continuous pattern using an electronic speed controller to cause the motor to rotate continuously.

For BLDC motors to operate, they constantly generate magnetic fields that switch both direction and origin. As the size of the motor increases so does the amount of current required and along with that so do magnetic fields. However, the current changes with the torque desired changes, which varies with the desired rotation rate. Thus, the magnetic fields generated by BLDC are highly variable and also vary in amplitude as the rotation rate changes. These magnetic fields are most often far stronger than the Earth’s magnetic field and thereby skew the readings taken by the magnetometers used on aircraft to determine their orientation, which are an integral part of their attitude and heading reference system (AHRS).

In order to understand the extent to which electric motors affect measurement, the UIUC Aero Testbed [8], which is a large fixed wing electric UAV, was held stationary and tested run. The results of the static run can be seen in Figure 2 and 3. Between 200 and 300 seconds, the batteries were installed in the aircraft with the motor switch turned off, this led to some slight vibration and motion being created. At around 670 seconds, the motor switch was turned on, with power flowing to the motors controller, however no power was applied to the motor to rotate. The motor was then run to full speed at 1405 seconds and then to zero speed at 1421 sec.

Figure 2 shows that there are no magnetic field affects to the accelerometers and the gyroscopes, as is expected. The accelerometer and the gyroscope output only shows noise and motion due to aircraft handling and motor vibration. The AHRS’s magnetometer and the resultant heading estimation readings were highly influenced by the induced magnetic field. When the motor was turned on, there was a difference of between 0.04 to 0.09 magnetic field units for each axis, from their previous values, which correlates to a heading change of 16 deg. Then, when the motor is run, as can be seen in Figure 3, the magnetic field readings differed by up to 2.0 magnetic field units from their previous values, which correlates to a heading change of up to 360 degrees. It should be noted that the AHRS outputs the magnetic field strength in arbitrarily value units which sum to approximately 1.3 when only subjected to the Earth’s magnetic field.

IV. STRATEGY

In order to provide high fidelity state estimation, the large deviations in attitude caused by the induced magnetic field must be corrected. As mentioned in Section III, there have been a variety of different methods used to apply corrections to magnetometer reading. All of methods are effectively based upon providing a predicting the magnetic field offset that is required to correct the readings, whether it be a constant offset or dependent on current use. These methods all require a good amount of calibration and their performance is based upon how well the calibration was done.

We propose a sensor fusion algorithm to correct the erroneous attitude determination using an integration method that discounts the readings taken by the magnetometer for an appropriate period of time. However, we will first define two cases where it would and would not be the best to use this method. The two cases are: level flight and agile flight.

In level flight it is assumed that the aircraft has a constant heading and velocity. The aircraft, for all practical purposes, remains in the same orientation with the horizon, so the roll and pitch angles are zero and the yaw angle will be constant, and travels in the direction of the aircraft is oriented, so the side slip angle and angle of attack will approximately be zero. This case is trivial as the heading of the aircraft could easily be found without the use of a magnetometer. Since the aircraft is oriented in the direction it is traveling, the orientation could be found from the aircraft’s velocity vector which is be measured by the AHRS’s global positioning system (GPS). Thus, there is no reason to use any other method to find the aircraft’s attitude.

In agile flight, however, the aircraft does not have a constant heading or velocity. The aircraft’s roll, pitch, and yaw angles cannot be assumed to be constant nor can the aircraft be assumed to travel in the direction the aircraft is oriented, so the side slip angle and angle of attack are not zero so finding the attitude using the aircraft’s velocity vector is not possible. Also, given the nature of this type of flight, getting consistent GPS position and velocity information can problematic as the GPS reliaver is often not facing the sky during agile maneuvers and therefore gets erroneous readings. In this case, since the
throttle and therefore motor current changes during maneuvers, the induced magnetic field generated by the motor changes thereby causing the calculated attitude to change independent of the aircraft’s actual attitude changes. The combination of the two flawed measurements almost guarantees that Extended Kalman filter (EKF) in the AHRS will not work properly. Therefore, the proposed integration method is well suited to correct the erroneous attitude determination of this flight case. The proposed sensor fusion algorithm works as following. A point in the flight path where the AHRS EKF state can be trusted will be used as a starting point. This starting point will be chosen so that it occurs right before the aircraft’s agile maneuver, thereby minimizing the time between trusted state data and likely erroneous state data. From that point forth, the AHRS accelerometer and gyro sensor outputs are time-step integrated to give the attitude and position of the aircraft. No magnetometer or GPS readings will be used as they cannot be trusted. This method will produce a flight state which is accurate within the AHRS accelerometer and gyro sensor noise. Thus, during the agile maneuver, the integration method will use only inertial sensors and since these sensors are not effected by external sources, the solution can be trusted. Once the aircraft returns to flight were the readings can be trusted, the state will again be acquired from the EKF in the AHRS.
relationship between the two reference frames are set by the sensor fusion algorithm. The AHRS accelerometer and gyro output is time-step integrated for all time in the maneuver. Two reference frames are used throughout the routine: an inertial world-frame (North-East-Down) and an aircraft body frame (defined by an axes system with $x$ out the nose and $y$ out the right wing). The simple trapezoidal rule was used to time-step integrate, however, better numerical integration schemes can easily be applied. 

The step-by-step routine is as follows:

1) Input the state data collected during the maneuver, either in real-time or in post-processing.

2) Clear erroneous measurements and replace with previous measurements.

3) Numerically integrate position and attitude:

   a) Set the start point using the initial position ($x$, $y$, $z$), world-frame velocities ($\dot{x}$, $\dot{y}$, $\dot{z}$), body-frame accelerations ($A_x$, $A_y$, $A_z$), attitude ($\phi$, $\theta$, $\psi$), and body-frame rotation rates ($p$, $q$, $r$) and find the body-frame velocities ($U$, $V$, $W$) and world-frame accelerations ($\ddot{x}$, $\ddot{y}$, $\ddot{z}$).

   b) Integrating for all time-steps, where primed variables represent the current time-step and un-primed variables represent the previous time-step:

      i) Find the world-frame rotation rates ($\dot{\phi}'$, $\dot{\theta}'$, $\dot{\psi}'$) from the body-frame rotation rates ($\dot{\phi}$, $\dot{\theta}$, $\dot{\psi}$) using the angular rate rotation matrix, $D^2$:

         \[
         \begin{bmatrix}
         \dot{\phi}' \\ \dot{\theta}' \\ \dot{\psi}'
         \end{bmatrix} = \begin{bmatrix} p' \\ q' \\ r'
         \end{bmatrix}
         \]

         where

         \[
         D(\phi, \theta, \psi) = \begin{bmatrix}
         1 & \sin \phi \tan \theta & \cos \phi \tan \theta \\
         0 & \cos \phi & -\sin \phi \\
         0 & \sin \phi \sec \theta & \cos \phi \sec \theta
         \end{bmatrix}
         \]

      ii) Find the start point body-frame velocities ($U$, $V$, $W$) from the world-frame velocities ($\dot{x}$, $\dot{y}$, $\dot{z}$) using the inertial to body rotation matrix, $R_B^I(\phi, \theta, \psi)$:

         \[
         \begin{bmatrix}
         U \\
         V \\
         W
         \end{bmatrix} = R_B^I(\phi, \theta, \psi) \begin{bmatrix}
         \dot{x} \\
         \dot{y} \\
         \dot{z}
         \end{bmatrix}
         \]

      iii) Find the start point world-frame accelerations ($\ddot{x}$, $\ddot{y}$, $\ddot{z}$) from the body-frame accelerations ($A_x$, $A_y$, $A_z$) using the body to inertial body rotation matrix, $R_B^I$, while correcting for gravity and IMU location offset$^1$ using a radius coefficient matrix, $C_{IMU}$, the body-frame rotation rates ($p$, $q$, $r$) and the body-frame velocities ($U$, $V$, $W$):

         \[
         \begin{bmatrix}
         \ddot{x} \\
         \ddot{y} \\
         \ddot{z}
         \end{bmatrix} = R_B^I(\phi, \theta, \psi) \begin{bmatrix}
         A_x \\
         A_y \\
         A_z
         \end{bmatrix} + \begin{bmatrix}
         0 \\
         0 \\
         g
         \end{bmatrix} + C_{IMU} \begin{bmatrix}
         p \\
         q \\
         r
         \end{bmatrix} \times \begin{bmatrix}
         U \\
         V \\
         W
         \end{bmatrix}
         \]

         where $R_B^I$ is equal to the inverse of $R_B^I$:

         \[
         R_B^I = R_B^I^{-1}
         \]

\[1\] Essentially we are removing the acceleration effects of rigid body rotation on the IMU, which is offset from the center of gravity

\[2\] The angular rate rotation matrix from the last time-step, $D(\phi, \theta, \psi)$, is used because new attitude values are not yet available and since the time-steps are assumed to be very small, there is negligible difference in values.
ii) Find the attitude \((\phi', \theta', \psi')\) by time-step integrating the world-frame rotation rates \((\phi, \theta, \psi)\):
\[
\begin{bmatrix}
\dot{\phi}' \\
\dot{\theta}' \\
\dot{\psi}'
\end{bmatrix} = \frac{1}{2} \left\{ \begin{bmatrix}
\dot{\phi}' \\
\dot{\theta}' \\
\dot{\psi}'
\end{bmatrix} + \begin{bmatrix}
\dot{\phi} \\
\dot{\theta} \\
\dot{\psi}
\end{bmatrix} \right\} \Delta T + \begin{bmatrix}
\dot{\phi} \\
\dot{\theta} \\
\dot{\psi}
\end{bmatrix}
\]
(8)

iii) Find the world-frame accelerations \((\ddot{x}', \ddot{y}', \ddot{z}')\) from the body-frame accelerations \((A'_x, A'_y, A'_z)\) using the body to inertial body rotation matrix \(R_B^W(\phi', \theta', \psi')\), while correcting for gravity and IMU location offset using a radius coefficient matrix, \(C_{TIMU}\), the body-frame rotation rates \((p', q', r')\) and the body-frame velocities \((U', V', W')\):
\[
\begin{bmatrix}
\ddot{x}' \\
\ddot{y}' \\
\ddot{z}'
\end{bmatrix} = R_B^W(\phi', \theta', \psi') \begin{bmatrix}
A'_x \\
A'_y \\
A'_z
\end{bmatrix} + \begin{bmatrix}
0 \\
0 \\
g
\end{bmatrix} \\
+ C_{TIMU} \left\{ \begin{bmatrix}
p' \\
q' \\
r'
\end{bmatrix} \times \begin{bmatrix}
U \\
V \\
W
\end{bmatrix} \right\}
\]
(9)

iv) Find the world-frame velocities \((\dot{x}', \dot{y}', \dot{z}')\) by time step integrating the world-frame accelerations \((\ddot{x}', \ddot{y}', \ddot{z}')\):
\[
\begin{bmatrix}
\dot{x}' \\
\dot{y}' \\
\dot{z}'
\end{bmatrix} = \frac{1}{2} \left\{ \begin{bmatrix}
\ddot{x}' \\
\ddot{y}' \\
\ddot{z}'
\end{bmatrix} + \begin{bmatrix}
\dot{x} \\
\dot{y} \\
\dot{z}
\end{bmatrix} \right\} \Delta T + \begin{bmatrix}
\dot{x} \\
\dot{y} \\
\dot{z}
\end{bmatrix}
\]
(10)

v) Find the body-frame velocities \((U', V', W')\) from the world-frame velocities \((\dot{x}', \dot{y}', \dot{z}')\) using the inertial to body rotation matrix \(R_B^W(\phi', \theta', \psi')\):
\[
\begin{bmatrix}
U' \\
V' \\
W'
\end{bmatrix} = R_B^W(\phi', \theta', \psi') \begin{bmatrix}
\dot{x}' \\
\dot{y}' \\
\dot{z}'
\end{bmatrix}
\]
(11)

vi) Find the world-frame position \((x', y', z')\) by time step integrating the world-frame velocities \((\dot{x}', \dot{y}', \dot{z}')\):
\[
\begin{bmatrix}
x' \\
y' \\
z'
\end{bmatrix} = \frac{1}{2} \left\{ \begin{bmatrix}
\dot{x}' \\
\dot{y}' \\
\dot{z}'
\end{bmatrix} + \begin{bmatrix}
\dot{x} \\
\dot{y} \\
\dot{z}
\end{bmatrix} \right\} \Delta T + \begin{bmatrix}
x \\
y \\
z
\end{bmatrix}
\]
(12)

VI. EVALUATION

In order to properly evaluate the performance of the sensor fusion algorithm an agile maneuver was performed with using an instrumented aircraft. The agile maneuver chosen to evaluate the algorithm was a loop, which is a fundamental aerobatic maneuver where the aircraft performs a vertical circle. The aircraft enters by flying straight and level, then pitches up through a circle while keeping the wings level and at a constant speed, and finally returns to level flight. In order to maintain constant speed throughout the loop, the throttle input must vary as a function of the aircraft’s angle with the ground. The loop provides the perfect maneuver to evaluate the algorithm in that the motor throttle changes, and so does the induced magnetic field; and in that the GPS receiver is not facing the sky for half of the maneuver where the aircraft is inverted, thereby yielding faulty readings.

A fixed-wing trainer-type radio control aircraft was built for testing the sensor data acquisition unit [7]. The aircraft built was a Great Planes Avistar Elite [9], which has a 62.5 in wingspan and a weight of 8.7 lb. The completed flight-ready aircraft is shown in Figure 5, its physical specification are given in Table II, and its airframe component specification are given in Table III. The aircraft was instrumented with the sensor data acquisition unit along with suite of sensors. Specification of the instrumentation installed in the Avistar is given in Table IV.

The instrumented Avistar aircraft was brought to a model airplane field and flown through a handful of loop maneuver
TABLE III: Avistar aircraft airframe component specifications

| Construction | Built-up balsa and plywood structure, aluminum wing tube, aluminum landing gear, abs canopy, and plastic film sheeted. |
| Flight Controls | Aileron (2), elevator, rudder, throttle, and flaps (2) |
| Transmitter | Futaba T14MZ [10] |
| Receiver | Futaba R6014HS |
| Servos | Futaba S3004 |
| Regulator Distribution | Castle Creations CC BEC [11] |
| Receiver Battery | Thunder Power ProPower 30c 4S 14.8 V 5 Ah lithium |
| Propulsion | Castle Creations Phoenix ICE 75 Amp Brushless Speed Controller [11] |
| Motor | AXI 4120/14 Outrunner [13] |
| ESC | Castle creation Phoenix ICE 75 Amp Brushless Speed Controller [11] |
| Motor Flight Pack | Thunder Power ProPower 30c 4S 14.8 V 5 Ah lithium polymer battery [12] |
| Flight Time | 10-20 min |

TABLE IV: Specifications of the sensor data acquisition unit and sensors installed in the Avistar

| Processing unit | BeagleBone running 32-bit Ubuntu Linux |
| Sensors | AHRS Xsens Mu-g 6-Dof IMU with W-Sys WS3910 GPS Antenna |
| Airspeed probe | EagleTree Systems Pitot-static probe |
| Airspeed sensor | All Sensors 20xH2O-D1-4V-MINI differential pressure sensor |
| Magnetometer | PNI Corp MicroMag 3 |
| Analog-to-digital converters | 2x Gravitech 12 bit - 8 Channel ADC |
| Power | Regulators Castle Creations CCBEC |
| Batteries | Thunder Power ProLine 2S 450 mAh |
| Transceiver | Digi 9X Tend 900-MHz card |
| Data Storage | 8GB microSD card |
| Data Rate | 100 Hz |

circuits. The circuits started with motor-off gliding flight where there is negligible motor induced magnetic fields and the GPS receiver is facing up; during this segment the AHRS can be trusted to produce accurate state estimation. The aircraft is then brought to motor-on level flight followed by the loop maneuver. After the loop, the aircraft finishes the circuit by again being flown with the motor off such that the AHRS can be trusted to produce accurate state estimation. The beginning and ending parts of the circuit contain flight segments where the state estimation provided by the AHRS can be trusted.

Evaluation of the sensor fusion algorithm occurred by comparing the end state of the circuit computed with that produced by the AHRS, given the same start state and all the intermediary inertial measurements. For ease of implementation, the sensor fusion algorithm was run off-line, however, there are no differences whatsoever in application of the algorithm: each time step is performed using only past state knowledge, as is available in on-line execution. The state estimates from the AHRS and the sensor fusion algorithm for a loop circuit are plotted in Figure 6 and the resultant flight paths were plotted in Figure 7. It should be noted that there was wind on the day of measurement that drifted the aircraft sideways during the maneuver.

Figure 6 (a) shows the aircraft’s Northing, Easting, and vertical position curves for both the AHRS and sensor fusion algorithm. Each respective set of curves start and remains together for the initial motor-off flight segment and returns to being together for the ending motor-off flight segment. The correlation between the sensor fusion algorithm and the AHRS at the start and end segments supports the fidelity of the sensor fusion algorithm. The curves for the aircraft’s attitude in Figure 6 (b) and the curves for the aircraft’s velocities in Figure 6 (c) likewise support the correctness of the proposed sensor fusion algorithm. Figure 6 (d)-(f) are provided to show raw data output from the accelerometer and gyroscope, which is used by the AHRS and the sensor fusion algorithm.

A trajectory plot of the AHRS position and attitude is given Figure 7 (a). As can be noted, the discussed sources of noise induce faulty measurements that result in visible miscalculations of aircraft attitude along its path. In the figure, two evident problems can be noted: (1) that the reconstructed aircraft’s attitude is not tangent to the flight path, representing an invalid physical behavior; and (2) that the reconstructed path appears as a segmented line, again suggesting unrealistic sudden changes in aircraft’s attitude.

Conversely, Figure 7 (b), shows a trajectory plot for the same flight obtained by applying the proposed sensor fusion algorithm. As can be noted, none of the aforementioned undesirable artifacts is visible on the reconstructed flight path. In addition, the trajectories in Figure 7 (a) and (b) show coherence in the the starting and ending segments of the flight path (points where state data from the AHRS can be trusted). Finally, we were able to estimate that the absolute position of the aircraft as produced by our sensor fusion algorithm revealed an accuracy within a meter, which, considering the spatial range used for the experiment, can be translated in a error factor as low as 1/4%.

VII. CONCLUSION

We have implemented the proposed sensor fusion algorithm that corrects erroneous attitude determination using a lightweight integration method. The validity of our algorithm was demonstrated using real flight data from an agile aeronautic maneuver. The sensor fusion algorithm was also shown to outperform an extended-Kalman filter in determining the aircraft’s state.

In addition, we have thoroughly investigated the negative effects caused by electric motor induced magnetic fields. Specifically, we determined the amount of interference that is introduced into the sensor measurements as well as to EKF state estimation.

In future work, we plan to demonstrate our sensor fusion algorithm on an aircraft in real-time. We also plan to further investigate other faulty-sensor data correction methods using measurements from different/redundant units, and this work can be expanded to collaborative flight of UAVs exchanging locally computed state variables.
Fig. 6: AHRS and sensor fusion (integration method) aircraft state estimates
Fig. 7: Flight path plot from state estimates (the aircraft is drawn six times larger than actual scale and once every second).
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REFERENCES


