A Comparative Evaluation of Low-Cost IMUs for Unmanned Autonomous Systems

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Abstract—Inertial measurement units (IMUs) are widely used for navigation and calibration purposes on unmanned autonomous vehicles. This paper provides a comparative survey and evaluation of the low-cost IMUs focusing on both the possible sensor packages and the available software solutions. Several example IMUs are compared in detail including inertial only IMUs, GPS-coupled IMUs, and hobbyist-level IMUs. The future direction of low-cost IMUs are discussed including optical-flow-based solutions and collaborative IMUs.

I. INTRODUCTION

An inertial measurement unit (IMU) is a device to measure the relative states of a static or mobile unit with respect to the inertial reference frame. Recently, many micro electro mechanical systems (MEMS) IMUs have emerged for only several hundred US dollars [1]. These low-cost IMUs can be used on unmanned vehicles for navigation [2], or can be combined with imaging sensors for georeferencing purposes. For example, the accurate orientation data is needed for the interpretation of the images from an airborne LIDAR radar. Actually, an accurate IMU accounts for a large portion of the total cost for an unmanned autonomous system [3].

The emergence of low-cost IMUs makes it possible to use more unmanned vehicles for agricultural or environmental applications like precision farming and real-time irrigation control [4], [5]. With the current trend of modularization and standardization in the unmanned system design, the developers can either use a cheap commercial-off-the-shelf (COTS) IMU as a part of the navigation system, or develop their own system with low-cost inertial sensors.

In this paper, the low-cost IMUs are defined as those with the price around or less than $3000. Low-cost MEMS IMUs are widely used on small or micro unmanned vehicles since they are small, light, yet still powerful. However, these cheap IMUs have bigger measurement errors or noise compared with expensive navigation grade or tactical grade IMUs [6]. It is challenging to design, test, and integrate these low-cost inertial sensors into a powerful IMU for navigation uses. More considerations for system design and sensor fusion algorithms need to be addressed to achieve autonomous navigation missions.

IMUs are usually used to measure the vehicle states like orientation, velocity, and position. The orientation measurement is especially important for missions requiring accurate navigation. However, the orientation is not directly measurable with the current COTS MEMS sensors. It has to be estimated from a set of correlated states like angular rates (gyros), linear accelerations (accelerometers), and magnetic fields (magentometers). Therefore, the estimation accuracy of IMUs heavily relies on the sensor fusion algorithm. Many researchers have looked into the state estimation problem using nonlinear filtering techniques [7]. Different kinds of Kalman filters are widely used in the aeronautics societies for spacecraft attitude estimations [8]. However, many of these algorithms are developed for highly accurate inertial sensors. Besides, those algorithms may have high demands for the computational power, which may not be possible for low-cost IMUs. The sensor fusion algorithms based on low-cost IMUs are focused in this paper. A short survey of the current available state estimation filters for low-cost unmanned autonomous systems is provided with several representative examples like complementary filters [9], extended Kalman filters [10], [11], [12], and other nonlinear filters [13].

The major contributions of this paper are to provide a comparative evaluation of current low-cost IMUs including both possible sensor packages and several representative sensor fusion algorithms. Unmanned system developers can either choose one suitable for their specific applications or develop their own IMU with similar inertial sensors. More importantly, several representative low-cost IMUs are thoroughly compared and evaluated.

The paper is organized as follows. The IMU basics and notations are introduced first in Sec. 2. The possible sensor packages are then explained with an emphasis on the possible measurement errors in Sec. 3. In Sec. 4, several representative state estimation algorithms for small UAVs are shown in detail. The example low-cost IMUs are compared and evaluated in Sec. 5. Finally, the future direction of low-cost IMUs and conclusions are provided.

II. IMU BASICS AND NOTATIONS

Most IMUs are employed for the measurement of the movements of a craft or a vehicle in 3D space. To describe the vehicle movements in 3-D space, the coordinate frames are defined as follows, shown in Fig 1:

(1) Vehicle Body Frame: $F_{body}$, the reference frame with the origin at the gravity center and the axes pointing forward, right and down.
(2) Inertial Navigation Frame: $F_{nav}$, the reference frame with a specific ground origin and the axes pointing the North, East and down to the Earth center.

(3) Earth-Centered Earth-Fixed (ECEF) Frame: $F_{ECEF}$, the reference frame with the origin at the Earth center. The $z$ axis passes through the north pole, the $x$ axis passes through the equator at the prime meridian, and the $y$ axis passes through the equator at 90° longitude.

Instead of making a direct measurement, IMUs rely on the sensor fusion algorithm to provide an accurate estimation of the system states. More precisely, the following states need extra estimation since no direct measurements are available or the update rate is not fast enough:

1. Position: the position information can greatly affect the georeferencing result. However, civilian GPS receivers can only provide measurements at 4-10 Hz or slower with the 3D accuracy of no less than three meters;
2. Attitude: the orientation information is very important for both flight control and image georeferencing;
3. Velocity: the ground velocity of the autonomous vehicle from GPS can not be updated fast enough for many applications.

The available direct measurements for low-cost IMUs include:

1. Position: for example longitude ($p_x$), latitude ($p_y$), altitude ($h$) (LLH) from GPS in 4-10 Hz or lower, the altitude or height can also be measured by pressure or ultrasonic sensors;
2. Velocity: ground speed from GPS ($v_n$, $v_e$, $v_d$) and the air speed from pressure sensors;
3. Rate gyro: angular velocity expressed in the body frame ($\dot{\psi}$, $\dot{\theta}$, $\dot{\phi}$);
4. Acceleration: linear acceleration expressed in the body frame ($a_x$, $a_y$, $a_z$).

The sensor fusion problem is defined as making an optimal estimation of the required vehicle states with the direct measurements from multiple sensors. This problem is also called a state estimation or a nonlinear filtering problem [7]. There are many possible solutions to this problem such as Kalman filters or complementary filters.

III. SENSOR PACKAGES

The developments of the low-cost MEMS inertial sensors can be traced back as early as 1970s [6]. In this section, the possible sensor packages for IMUs are introduced with an emphasis on the error models and the IMU categories.

a) Gyro: A gyro sensor is to measure the angular rate around the pre-specified axis observed from the earth coordinated in the body frame. Most manned or unmanned aircraft have three-axis gyros onboard. The gyro error model can be expressed as:

$$\dot{\omega} = (1 + s_g)\omega + b_g + \mu_g, \quad (1)$$

where $\dot{\omega}$ is the measurement value, $s_g$ is the scale error, $\omega$ is the true value, $b_g$ is the gyro bias, and $\mu_g$ is the random noise. Gyro sensors can be integrated to get the estimate of the angle. However, angle estimates based only on gyros have big drifts since the gyro bias is integrated over the time.

b) Accelerometer: Accelerometers used on low-cost IMUs are to measure the linear acceleration. In fact, accelerometers measure the acceleration minus the gravity vector. For example, the default output of the accelerometer (static) is -1 when the axis is pointing down into the earth center.

$$\dot{a} = (1 + s_a)a + b_a + \mu_a, \quad (2)$$

where $\dot{a}$ is the measurement value, $s_a$ is the scale error, $a$ is the true value, $b_a$ is the accelerometer bias, and $\mu_a$ is the random noise.

The accelerometer can also be used to measure the vehicle attitude since three-axis accelerometers can measure the gravity vector under the condition of zero acceleration. However, angle estimates from accelerometers suffer from high frequency noise when the unmanned vehicles are moving.

c) Magnetometer: Magnetometers are to measure the magnetic fields of the Earth, which can be approximated as an absolute value assuming the vehicle is not moving too fast. Three-axis magnetometer can be used for heading estimation and gyro bias compensation. One disadvantage of magnetometer sensors is that the hard-iron and soft-iron calibrations are needed for every vehicle.

d) GPS: GPS sensors can provide measurements of the absolute position, velocity, and course angle. The position packets can either be latitude, longitude, height (LLH) or $x$, $y$, $z$ expressed in the ECEF frame. The velocities include $v_n$, $v_e$, $v_d$, all with respect to the inertial frame. The course angle is defined as the angle relative to the north clockwise [14]. The GPS measurements have advantages of bounded errors, which can be used to reset the system error infrequently. The disadvantages of GPS include low update rate (<4 Hz mostly) and vulnerability to weather and terrain interference.

e) Pressure Sensor: Pressure sensors include absolute pressure sensors and relative pressure sensors. The former can be used to measure air pressure and to estimate the altitude. The latter can be used to measure air speed, which is especially useful to unmanned aerial vehicles.

Based the performance and the characteristics of the above sensors, the commercial inertial measurement units...
(IMUs) can be categorized into four types: navigation grade, tactical grade, industrial grade, and hobbyist grade. It is worth mentioning here that most of the industrial grade and hobbyist grade IMUs use MEMS inertial on-chip sensors, which greatly reduce the unit sizes and weights. The brief specifications are shown in Table I. It can be seen that low-cost IMUs mostly fall into the industrial grade or the hobbyist grade due to their low cost and bigger errors compared with navigation or tactical grade IMUs.

IV. ATTITUDE ESTIMATION ALGORITHMS

Given the above sensor packages, an efficient sensor fusion algorithm is needed for the optimal estimation of the vehicle attitude. Extended Kalman filters are frequently used in nonlinear estimation problems, especially attitude estimation problems of rigid bodies like a spacecraft or an aircraft. The extended Kalman filter can recursively estimate the system states from system measurements corrupted with Gaussian noises. It has advantages here since both gyro and accelerometer sensors have drifts and Gaussian-like noises. The general extended Kalman filter and three representative approaches for the attitude estimation problem are introduced in the following sections.

A. General Extended Kalman Filter

Assume that a general nonlinear discrete-time system can be modeled as follows:

\[ x_k = f(x_{k-1}, u_k) + w_k, \quad s.t. \quad w \sim N(0, Q), \]
\[ y_k = g(x_k) + v_k, \quad s.t. \quad v \sim N(0, R), \]

where \( x_k \) is a \( m \times 1 \) vector, \( y_k \) is a \( n \times 1 \) vector, \( f(x_{k-1}, u_k) \) and \( g(x_k) \) are nonlinear functions. The first equation is called the propagation equation and the second one is called the measurement equation.

Given the initial values \( P_0 \), the measurement covariance \( R \) and the state covariance \( Q \), the optimal Kalman estimate of the states can be updated using the following steps [15]:

1) State estimation extrapolation: \( \hat{x}_{k|k-1} = f(x_{k-1|k-1}, u_k) \),
2) Error covariance extrapolation: \( P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \),
3) Kalman gain: \( K_k = P_{k|k-1} G_k (G_k P_{k|k-1} G_k^T + R_k)^{-1} \),
4) State estimate update: \( \hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k (y_k - g(x_{k|k-1})) \),
5) Error covariance update: \( P_{k|k} = (I - K_k G_k) P_{k|k-1} \).

The \( P_k \) is the Jacobian matrix of \( f(x_{k-1}, u_k) \), and the \( G_k \) is the Jacobian matrix of \( g(x_k) \).

B. Quaternion-Based Extended Kalman Filter

Unit quaternions have many applications in state estimation problems because their simplicity. A quaternion-based extended Kalman filter was proposed originally for the MNAV IMU from Crossbow Technology [12]. UAV developers have used this approach on their specific platform [16].

The system state variables include both the unit quaternion \( q \) and the gyro biases \( (b_p, b_q, b_r) \). The measurements or observation of the system are the accelerations: \( a_x, a_y, a_z \), and the yaw angle \( \psi \) derived from the magnetometer.

The propagation equation and the measurement equation are listed below [12].

\[ q = \frac{1}{2} \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \dot{\hat{q}} \\ \dot{\hat{\hat{q}}} \\ \dot{\hat{\hat{\hat{q}}}} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} + w_k, \quad q + w_k, \quad \text{(5)} \]

\[ q = \begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \\ b_p \\ b_q \\ b_r \end{bmatrix} = \begin{bmatrix} \hat{\theta} \\ \hat{\psi} \\ \hat{\phi} \end{bmatrix} = \begin{bmatrix} p \\ q \\ r \end{bmatrix} - \begin{bmatrix} b_p \\ b_q \\ b_r \end{bmatrix}, \quad \text{(6)} \]

where \( w_k \sim N(0, Q) \), \( v_k \sim N(0, R) \).

It is worth pointing out that the measurement equation has an assumption that the acceleration measured is only the projection of the gravity vector. However, this assumption may not be true for small UAVs.

C. Euler Angle-Based Extended Kalman Filter

Euler angles can also be chosen as the system states for the attitude estimation problem. Assuming that the system state is a vector \( x \) (representing the roll and pitch angle) and the system output is a vector \( \hat{y} \) (representing the accelerometer readings), the system can then be modeled [17]:

\[ x = \begin{bmatrix} \phi \\ \theta \\ \psi \end{bmatrix}, \quad \hat{y} = \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix}, \quad \text{(8)} \]

\[ \hat{x} = \begin{bmatrix} \dot{p} \\ \dot{q} \\ \dot{r} \end{bmatrix} = \begin{bmatrix} p + q \sin \theta \tan \theta + r \cos \theta \tan \theta \\ q \cos \phi - r \sin \phi \end{bmatrix} + v_w, \quad \text{(9)} \]

\[ \dot{\psi} = \begin{bmatrix} \dot{\psi} \\ \dot{\phi} \end{bmatrix} = \begin{bmatrix} \dot{a} - r v + q w - g \sin \theta \\ \dot{w} - p v - g \cos \theta \sin \phi \end{bmatrix} + v_k, \quad \text{(10)} \]

where \( v_w \sim N(0, Q) \), \( v_k \sim N(0, R) \).

In fact, the velocities \( (u, v, w) \) are not easily measurable at high frequencies. The air speed can be used instead to simplify the measurement equation for small fixed-wing UAVs. The following assumptions can be made [17]:

- \( \dot{u} = \dot{\phi} = \dot{v} = 0 \). The small UAV will not accelerate all the time;
- \( v = 0 \). The small fixed-wing UAV will not go sideways;
- \( u = \dot{\phi} \cos \theta, \quad w = \dot{\phi} \sin \theta \);

where \( \dot{\phi} \) is the air speed measured by a pitot tube [10]. The
measurement equation can then be simplified [17].

\[
\hat{\mathbf{y}} = \begin{bmatrix}
qV_v \sin \theta + g \sin \theta \\
rV_a \cos \theta - pV_a \sin \theta - g \cos \theta \sin \phi \\
-qV_a \cos \theta - g \cos \theta \cos \phi
\end{bmatrix} + v_k (11)
\]

where \(v_k \sim N(0,R)\).

The attitude can then be estimated using the extended Kalman filter following the steps described in the above section.

D. AggieEKF: GPS Aided Extended Kalman Filter

AggieEKF, a GPS aided extended Kalman filter is proposed in this section with considerations from both filters designed in the above sections. An extended Kalman filter similar to the one in [12] is developed. However, the measurement equation is replaced by a more accurate estimation of the gravity vector with the help from the GPS speed measurements. The system equations are shown as below where \(V_e\) is the ground speed measured by the GPS.

\[
\dot{q} = \begin{bmatrix}
0 & -\dot{p} & -\dot{q} & -\dot{r} & 0 & 0 & 0 \\
\dot{p} & 0 & \dot{\phi} & 0 & 0 & 0 & 0 \\
\dot{q} & -\dot{r} & 0 & \dot{\phi} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix} q + w_k (12)
\]

\[
\begin{bmatrix}
\dot{a}_x \\
\dot{a}_y \\
\dot{a}_z
\end{bmatrix} = \begin{bmatrix}
2g(q_1q_3 - q_0q_2) \\
2g(q_2q_3 + q_0q_1) \\
g(q_0^2 - q_1^2 - q_2^2 + q_3^2)
\end{bmatrix} + v_k, \quad (13)
\]

where

\[
\begin{bmatrix}
\dot{a}_x \\
\dot{a}_y \\
\dot{a}_z
\end{bmatrix} = \begin{bmatrix}
a_x - rV_e + g \sin \phi_{-1} \\
a_y + qV_e + g \cos \phi_{-1}
\end{bmatrix}, \quad (14)
\]

and \(v_k \sim N(0,R)\). The attitude state estimation can be calculated using the steps described in the above section.

E. Complementary Filters

Aside of the Kalman filter approaches, there are other nonlinear filters like complementary filters. One example complementary filter is shown below [18]:

\[
\hat{R} = [(\Omega \times R) + k_{est} \pi_a(\hat{R}) \hat{R}^T]R, \quad (15)
\]

\[
\pi_a(\hat{R}) = \frac{1}{2} (\hat{R} - \hat{R}^T), \quad \hat{R} = \hat{R}^T R, \quad (16)
\]

where \(\Omega\) is the body angular velocity, \(R\) is the rotation matrix estimated from accelerometers, and \(k_{est}\) is the gain to tune. The key idea here is to fuse the estimation from gyros and from accelerometers [9].

V. EXAMPLE LOW-COST IMUS

Several example low-cost IMUs are compared in this section focusing on hardware sensors, estimation accuracy, and software modification ease. The detailed hardware specifications are compared in the end of this section.

A. Attitude Estimation IMUs

The Microstrain 3DM-GX2 IMU has typical inertial sensor sets including 3-axis gyros, 3-axis accelerometers, and 3-axis magnetometers [19]. The 3DM-GX2 IMU can output the angle estimations in either Euler angles or rotational matrix at up to 250 Hz and the sensor bandwidth is 100 Hz. The 3DM-GX2 IMU can be easily connected with other units through RS232/422 or USB interfaces. Another advantage of The 3DM-GX2 IMU is its resistance to shock interferences of up to 500g when powered. There are also similar IMUs like the 3DM-GX3 from Microstrain and VN100 from VectorNav Technologies [20].

B. GPS-Coupled IMUs

The GPS/inertial navigation system could be only one board or two separate units. Unfortunately, the GPS/INS integrated unit with the built-in sensor fusion algorithm is very expensive. The MTi-G IMU from Xsens has both attitude and position estimations at up to 120Hz, shown in Fig 3. However, this IMU costs a lot more than $3000. It is just shown here for comparison reasons.

A GPS-coupled IMU can also be combined with two isolated units (GPS and IMU) and a central processor. AggieNav is built in Center for Self-Organizing and Intelligent Systems (CSOIS) at Utah State University following this idea [22]. Based around Analog Devices’ ADIS1635X 6-DOF IMU part, AggieNav includes a GPS unit, a magnetic
compass, as well as pressure sensors for airspeed measurement. AggieNav also has a Gumstix Verdex Pro connected for heavy computations like further processing of the sensor data, and greater control over other aspects of the UAV mission.

C. Hobbyist Grade IMUs

Recently, several hobbyist grade IMUs have become available with “flat” three-axis gyros and accelerometers. Hobbyist grade IMUs can also be used by the hobbyist for the navigation mission of easy-configured UAVs [1].

Ardu-IMU is one representative IMU made from an open source project, shown in Fig. 5. It uses complementary filters derived from Mahony’s work [2]. It can output attitude estimates up to 50 Hz.

Sparkfun Razor IMU is another representative IMU made from “flat” three-axis sensors [23], shown in Fig. 6.

D. Comparisons

A detailed comparison of the specifications for all the IMUs mentioned above is provided in Table II. It is worth mentioning that several low-cost IMUs like Ardu IMU are using single-chip dual axis gyro sensors which is convenient for micro unmanned vehicles.

VI. Future Directions

Nowadays, inertial sensor and unmanned system technologies are undergoing great changes every year. There are still many new research ideas that can be tried on IMUs.

(1) Optical-Flow-Based IMU: Most birds rely on vision for navigation, which is the basic idea of the optical flow. With the improving accuracy of the optical flow chips, an optical-flow-based IMU can be expected soon.

(2) Accelerometer/gyro Network: Small size and wireless capabilities make it possible to employ a gyro or accelerometer network on the unmanned vehicles. The redundant sensors can be combined for an more accurate estimate.

(3) GPU: Most current IMUs are still more or less limited by the computational power. The graphics processing unit (GPU) can be put onboard to support intensive calculations such as real-time image processing for attitude estimations.

(4) Fractional Order Kalman Filter (FOKF): Fractional order Kalman filter can provide a different approach from the current nonlinear estimation algorithms. The reason is that most current extended Kalman filter approaches made an assumption that the sensor noise is Gaussian, which may not be true. FOKF could handle the non-Gaussian noise better because fractional order calculus assumes infinite dimensions.

(5) Collaborative IMUs: The low-cost IMUs and unmanned vehicles introduce a new challenge on how to optimize the IMU capabilities among a heterogeneous UAV group with different types of IMUs. A leader UAV with a high accuracy IMU can send messages to the follower UAVs with low-cost IMUs for estimation improvements at a low frequency.
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