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A simplified approach to motion estimation in a UAV using two filters

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Abstract:
Considering the requirement of precision positioning of Unmanned Aerial Vehicles in applications like in flights formations and flights with collision avoidance, this paper presents the proposal of a composition of a Complementary Filter used in orientation estimation and a Linear Kalman Filter (KF) in position estimation of the UAVs. The data evaluated in the experiments were acquired post flight from the flight controller embedded in a UAV. An Inertial Measurement Unit is used to provide the essentials datasets to the implementation of the Complementary Filter, which is modelled by Euler Angles referenced in a North-East-Down (NED) Coordinate System. The position estimation is obtained using the data from Global Positioning System (GPS) allied to a barometer applied in a Position-Velocity-Acceleration (PVA) model with Linear Kalman Filter. The acquired results provide evidence of the suitability and soundness of the proposed approach.

Keywords: Pose Estimation, Kalman Filter, Sensor Fusion, Complementary Filter, Unmanned Aerial Vehicle.

1. INTRODUCTION

In the last decade 4-Rotor Unmanned Aerial Vehicles (UAVs) have gained popularity due to the simplicity in their construction, ease maintenance, as well as by their flexibility to reach difficult places to access, maneuverability, stability and Vertical Take-Off and Landing capabilities (Abas et al., 2013). They have being used in both civil and military applications such as surveillance, rescue, aerial imagery, structural inspection and maintenance. Due to their suitability and efficiency in accomplishing missions in the mentioned applications, they have received great attention and have been an important research topic (Teulière et al., 2010; Zhang et al., 2015).

One of the trend topics in the development of UAVs is related to state estimation. It covers both states of motion and posture information such as velocity, acceleration, heading, tilt and rotation angles. Also reliable motion control and pose estimation are basic requirements to achieve autonomous flight (Hong et al., 2014; Xu Wanli et al., 2014). The most common setting used to ensure a reasonable state estimation is the sensorial fusion. It could be seen as a process that utilizes data from one or more sensors to reduce the uncertainty of the others sensors measures. Filtering techniques are also used to improve the accuracy of the data acquired from sensors. An example of sensorial fusion is based on the Extended Kalman Filter (Gelb, 1974) applied to optimally fuse gyroscopes and accelerometer measurements (Abeywardena and Munasinghe, 2010).

The advances in aerial robotics research allowed multiple UAVs be cooperatively used to carry out tasks that can not be easily done by a single robot (Alejo et al., 2009). They use strategies known as tactics, which are defined as the procedure used by the UAV team to execute a mission and that can be either centralized, in which a decision maker sends coordinated instructions to a group of UAVs or decentralized, in which each of them is responsible for making its individual decisions. There are consistent tactics which can be classified as swarming or formation, task assignment, formation reconfiguration and dynamic encirclement and both of them require accurate pose estimation and collision avoidance methods to accomplish their tasks. (Hafez et al., 2015).

This work presents a position estimation strategy based in a random motion, considered as a Position-Velocity-Acceleration (PVA) model, using a Linear Kalman Filter together with the measurements of Global Positioning System (GPS) and Barometer to approximate the true movement. An approach to orientation estimation, based on a complementary filter performing sensorial fusion, will also be demonstrated.

This paper is structured as follows: Section 2 presents a literature review. In Section 3, the mathematical modelling and fundamentals of the proposed solution are demonstrated. The numerical results are presented and discussed in Section 4. Section 5 presents the conclusions and the directions for future works.

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2. RELATED WORKS

The pose estimation was treated in (Filipe et al., 2015) applying a Dual Quaternion Multiplicative Extended Kalman Filter (DQ-MEKF). This technique is an extension of the Quaternion Multiplicative Extended Kalman Filter (Lefferts et al., 1982) widely employed for spacecraft attitude estimation, using the dual quaternion multiplication and the concept of error unit dual quaternion.

In (Blachuta et al., 2014), the relationship between the measured signals, on each axis in the sensor coordinates, and the inertial coordinates were defined by the Euler angles, respectively by roll (ϕ), pitch (θ) and yaw (ψ) angles, as a specific sequence of rotation with respect to x, y and z axes of a referred coordinate system. The axes of inertial coordinate system were defined as a right handed Cartesian coordinate system with North, West and Upward (NWU) directions.

In (Huang et al., 2015), the Euler angles were utilized to find the transformation matrix which relates the North-East-Down (NED) frame and the body frame. Furthermore, the Euler angles were determined from the gyroscope, magnetometer and accelerometer to implement the Complementary Filter.

In (Challa et al., 2016), a quaternion-based attitude unscented Kalman filter was formulated with quaternion errors parametrized by small angle approximations considering a magnetometer-only spacecraft scenario. The method was applied to a filter with a state vector consisting of the attitude quaternion and the gyro bias vector.

A generalized complementary filter (GCF) was proposed by (LI, Xiang et al., 2015) for attitude estimation. The GCF was based on the vector observation and its cross product. The results from the GCF had better numerical stability and much higher computational efficiency than the multiplicative extended Kalman filter (MEKF).

3. METHODOLOGY

3.1 Position Estimation

The linear motion in each of the axis (x, y, z) was defined as a unidimensional random motion. The random motion was considered as a Position-Velocity-Acceleration (PVA) model. As could be seen in Fig. 1, the acceleration is modeled as the integral of the white noise (Brown and Hwang, 2012).

Since the model is based in a random walk process, it does not reflect the real movement of the UAV. The embedded sensors are therefore used to approximate the real motion based on PVA model.

In the considered PVA model where the input is a Gaussian noise, all states are non-stationary. Due to this fact and also according to (Brown and Hwang, 2012), this model is only useful in the cases where measurements can be used to bound the states.

A linear Kalman Filter (Kalman, 1960) was chosen to handle with the motion model. The process to be estimated in the filter was defined in the equation (1), where $\boldsymbol{\Phi}_k$ is the state transition matrix, $\boldsymbol{H}_k$ is the state observation matrix and $\boldsymbol{w}_k$ an $\boldsymbol{v}_k$ are both uncorrelated Gaussian white noise.

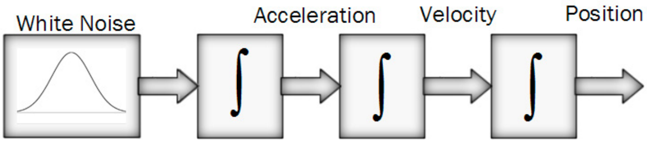

Fig. 1. Position-Velocity-Acceleration (PVA) Model (Brown and Hwang, 2012).

$$\begin{aligned} \boldsymbol{x}_{k+1} &= \boldsymbol{\Phi}_k \boldsymbol{x}_k + \boldsymbol{w}_k \\ \boldsymbol{z}_k &= \boldsymbol{H}_k \boldsymbol{x}_k + \boldsymbol{v}_k \end{aligned} \tag{1}$$

The linear motion state-vector (2) has nine states, where P defines position, V velocity and A acceleration for each axis. Following the basic concepts of kinematics and also to be consistent with equation (2), the state transition matrix $\boldsymbol{\Phi}_k$ (4) is derived for a particular unidimensional case from equation (3) and thus extended to three-dimensional case (Gibbs, 2011).

$$\boldsymbol{x}_k = \begin{bmatrix} Px_k & Py_k & Pz_k & Vx_k & Vy_k & Vz_k & Ax_k & Ay_k & Az_k \end{bmatrix}^T \tag{2}$$

$$\begin{bmatrix}\dot{P}\\ \dot{V}\\ \dot{A}\end{bmatrix} = \overbrace{\begin{bmatrix}0&1&0\\0&0&1\\0&0&0\end{bmatrix}}^{\mathbf{F}} \begin{bmatrix}P\\V\\A\end{bmatrix} + \begin{bmatrix}0\\0\\Q\end{bmatrix}$$

$$\boldsymbol{\Phi} = \mathbf{I} + \mathbf{F}\Delta t + \frac{(\mathbf{F}\Delta t)^2}{2} = \begin{bmatrix}1 & \Delta t & \frac{1}{2}\Delta t^2\\ 0 & 1 & \Delta t\\ 0 & 0 & 1\end{bmatrix} \tag{3}$$

The measurements utilized to bound the PVA model are acquired from a Global Positioning System (GPS) and also from a barometer sensor. The first of them is used to acquire latitude and longitude data and the other to acquire altitude data. The measurement vector $\boldsymbol{z}_k$ is defined as in the equation (5) where Px_{g_k} defines the latitude, in degrees, Py_{g_k} the longitude, in degrees, and Pz_{b_k} the altitude, in meters (AG, 2013).

$$\boldsymbol{\Phi}_k = \begin{bmatrix} \mathbf{I}_{3x3} & \Delta t * \mathbf{I}_{3x3} & \frac{1}{2}\Delta t^2 * \mathbf{I}_{3x3} \\ \mathbf{0}_{3x3} & \mathbf{I}_{3x3} & \Delta t * \mathbf{I}_{3x3} \\ \mathbf{0}_{3x3} & \mathbf{0}_{3x3} & \mathbf{I}_{3x3} \end{bmatrix}_{9x9} \tag{4}$$

$$\boldsymbol{z}_k = \begin{bmatrix} Px_{g_k} & Py_{g_k} & Pz_{b_k} \end{bmatrix} \tag{5}$$

North-East-Down (NED) Coordinate System The NED coordinate system is a coordinate frame fixed to the earth's surface. It is also known as ground or navigation coordinate system. In the Fig. 2 are defined the origin and axes from this coordinate system (Cai et al., 2011).