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Multiple model adaptive complementary filter for attitude estimation

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A B S T R A C T

Attitude estimation plays a major role in the autonomy of unmanned aerial vehicles and requires fusion of different sensor measurements. This paper describes an adaptive estimation scheme in which the weight parameter for the complementary filter (CF) is varied over time. The adaptive mechanism proposed here is inspired from the multiple model adaptive estimation (MMAE) scheme used for varying noise parameters in the Kalman filter structure. In this paper, linear complementary filters are used as elementary blocks in MMAE structure whose weights are modified probabilistically to obtain an accurate orientation estimate. It avoids the problem of manual selection of weight factor for complementary filter and provides a robust orientation estimate against varying system dynamics. The proposed MMAE based adaptive CF scheme is modular in nature and is dependent on the residual error between estimated and measured orientation angle. It is applied on the real world datasets logged from inertial sensors and the performance of MMAE based CF structure is found to work promisingly as compared to the non-linear complementary filter versions and the extended Kalman filter framework.

1. Introduction

Attitude estimation is one of the most important aspects required for the guidance and control of any moving vehicle. It is computed by taking cues from the sensors such as accelerometer, gyroscope and magnetometer, providing linear acceleration, angular velocity and magnetic field, respectively [1]. The sensor data is brought to the global reference frame by appropriate matrix conversions and is used to compute attitude [2]. Attitude estimators are widely used in various fields such as unmanned vehicle navigation [3], robotic manipulators [4,5], virtual reality, motion estimation for gait rehabilitation of patients [6,7], and navigation in GPS denied environments.

Among the several attitude estimators developed in the past, Kalman Filter (KF) and Complementary Filter are the two most popular sensor fusion schemes. Kalman filter has been used as a linear optimal estimator for wide range of problems and has undergone several advancements such as Extended Kalman Filter (EKF), Unscented Kalman Filter and Particle filter. However, Kalman filters are generally complex and require precise knowledge of process and measurement noise for a stable filter operation [9,10]. Instead, complementary filters are very simple and computationally efficient, and are used widely for task of estimating attitude of an unmanned aerial vehicle [4].

Complementary filters have been conceived long back by Wirkler in 1951 and has been used to fuse measurements with low and high frequency noise components obtained from two different sources [11]. Anderson and Fritze applied the CF approach for combining heading signal (with low frequency noise) and radio deviation signal (with high frequency noise) to obtain a better estimate of rate signal [12]. Complementary filter was also discussed in detail by several authors for application related to navigation and compared it with the Kalman filter [13,14]. Corke and Saripalli et al. proved the inability of linear CF to adapt to the varying bias of low cost sensors and prepared framework for non-linear complementary filter (NCF). Mahony et al. proposed a quaternion based nonlinear complementary filter for the estimation of attitude parameters, which has been very popular since then [15–17]. However, this non-linear CF technique cannot not provide reliable attitude estimate when the vehicle suffers from varying dynamics as the accelerometer does not provide stable low pass estimates [18]. Euston et al. proposed a NCF that uses the airspeed measurements and angle of attack along with the accelerometer and gyroscope measurements for attitude estimation. Several adaptation mechanism have been introduced in the literature which

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could provide adaptation to CF by either adjusting the cut-off frequency of the CF [19] or adjusting the gain parameters based on motion parameters [20] or acceleration dynamics [21]. Hong et al. proposed a variant of the NCF by adding an adapting the gain parameters through fuzzy rules [22]. This scheme has a disadvantage of being dependent on the membership function for fuzzy rules and does not provide desired estimation accuracy. Shen et al. in [23] incorporate simultaneous perturbation stochastic approximation (SPSA) optimization scheme to select an optimum parameter value of fuzzy membership function and is combined with the fuzzy logic rule to adapt the CF gain parameters according to dynamic situation. Tian et al. [24] and Poddar et al. [25] have applied optimization schemes to obtain the gain parameters of complementary filter automatically rather than experimenting via trial and error method.

Among the several efforts made by researchers in adapting the non-linear complementary filter, this paper aims at adapting the linear complementary filter. These LCFs has only one manually fed weight parameter unlike two gain parameters in the NCF and is found to have better estimation accuracy than the traditional NCF and extended Kalman filtering techniques. In this framework, the weighted sum of individual filters in the filter bank is combined together to provide an adaptive attitude estimate at each time instant. The proposed approach is inspired from the MMAE based adaptive Kalman filtering scheme in which the noise parameters are varied over time [27,28]. The Kalman filter block, generally used in the MMAE structure is replaced here with the linear complementary filter with different α parameters in each block. This scheme can adjust to the varying dynamics easily as the weightage of individual filter varies with the residual error between estimated and measured orientation angle.

The proposed approach of estimating attitude in case of varying dynamics is very much suitable to conditions where the flight suffers from the effect of the unknown external disturbances or unknown system uncertainty or varying actuator dynamics [29]. Near space vehicles are one of the modern aerospace vehicles, which are subject to failures arising from actuators, sensors or control surfaces. These failures/ faults need to be detected and estimated as early as possible for improving the overall efficiency of the system [30]. Although several fault detection and isolation techniques have been developed for nonlinear systems, a wide research is still under progress for fault identification and estimation in uncertain systems. Several techniques such as adaptive observers [31], supervised learning [32], sliding mode observers [33,34], adaptive sliding observers [30], fuzzy-logic based fault diagnosis [35,36], have been developed for the task of fault estimation. The multiple-model adaptive estimation (MMAE) framework has also been applied earlier for the task of fault detection and identification of flight vehicles [37–40]. However, a coherent framework of estimating attitude using complementary filter in uncertain systems, with different failure modules getting excited at different conditions is non-existent and can be explored further as future scope of this work.

The complete paper is organized as follows: Section 2 presents the theoretical background required for understanding the approach, Section 3 explains the proposed methodology where the usage of MMAE framework with linear complementary filter is described comprehensively. This is followed by the results and discussions section which provides detailed analysis of MMAE for CF using different datasets and compares it with other standard non-linear complementary filtering schemes and extended Kalman filter. And, finally Section 5 concludes the paper with future scopes of the present work.

2. Mathematical preliminaries

In this article, it is proposed to incorporate a weight adaptation mechanism for linear complementary filter using the MMAE concept which has been widely used for the task of adapting Kalman filter earlier. The MMAE based adaptive complementary filter proposed here replaces the EKFs in its structure with CF and has different gain values for different blocks. This section provides theoretical concepts related to orientation estimation from sensors, CF and MMAE algorithm and is provided for the sake of completion and a better comprehension of the ideas proposed in this paper.

2.1. Orientation from inertial sensors

The orientation of an object can be defined as the angular rotation about the three axes x, y, and z with reference to the global North-East-Down (NED) reference frame [41,42]. The inertial sensors, comprising of gyroscope and accelerometer along with magnetometer helps in obtaining these orientation angle at every time instant. The gyroscope reading provides the rate of change of angular orientation with respect to the body frame and are represented in the global frame as:

$$\dot{\phi} = p + q \sin\phi \tan\theta + r \cos\phi \tan\theta \tag{1}$$

$$\dot{\theta} = q \cos\phi - r \sin\phi \tag{2}$$

$$\dot{\psi} = q \sin\phi \sec\theta + r \cos\phi \sec\theta \tag{3}$$

Here, p, q, and r are the gyroscope readings and φ, θ, and ψ are the rotational angles about x, y, and z-axes, respectively and a dot over it represents their derivative. Upon integration, Eq. (1)–(3) provides the orientation angle which is usually mixed with low frequency drift and bias, leading to a large offset even if the sensor is stationary [17,43]. To compensate for the drift and bias errors, gyroscope estimates are generally fused with the estimates from the accelerometer and magnetometer. The equations for computing the roll, pitch and yaw angles from the accelerometer and magnetometer measurements are given as:

$$\phi_a = \tan^{-1}\left(\frac{a_y}{a_z}\right) \tag{4}$$

$$\theta_a = \tan^{-1}\left(\frac{-a_x}{a_y \sin\phi + a_z \cos\phi}\right) \tag{5}$$

$$\psi_m = \tan^{-1}\left(\frac{m_x \sin\phi - m_y \cos\phi}{m_x \cos\theta + m_y \sin\theta \sin\phi + m_z \sin\theta \cos\phi}\right) \tag{6}$$

Here, a_x, a_y, a_z are the accelerometer measurements and m_x, m_y, m_z are the magnetometer measurements. The subscript indicates the sensitive axis of measurement. Here, the effect of longitudinal and centripetal accelerations on the accelerometer measurements is ignored to compute the orientation angles.

Tseng et al. simulated the frequency response of the gyroscope, accelerometer and magnetometer and found the gyroscope sensor to have a complementary frequency response as compared to the other two sensors [43]. This creates an ideal situation for fusing information on one side from the gyroscope and on the other side accelerometer & magnetometer.

2.2. Complementary filter

It is a well-known sensor fusion technique to combine information from two modules which have a complementary frequency response to each other. The basic structure of the complementary filter is shown in Fig. 1. Here, x_1 and x_2 are the noisy versions of original signal x corrupted by high and low frequency noise, respectively such that when they are combined by passing through

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