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Modified Cascade Kalman Filter for Sensor Data Fusion in Micro Aerial Vehicle ⋆

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Abstract: Precise attitude estimation is important for navigation, guidance and control of Micro Aerial Vehicles (MAV) as they are mostly equipped with low integrity sensors due to the constraints on MAV payload and available power. The MAV sensors such as accelerometer and magnetometer are prone to noise as they are placed in proximity to the motor due to constraints on centre of gravity (CG). Data from a single sensor are not reliable for all operating points of flight envelope as the motor vibration and magnetic flux due to the motor vary with RPM. Hence accurate attitude estimation of MAV is achieved through multisensor data fusion. In this paper, a modification to the classical cascade Kalman filter is proposed. Modified Cascade Kalman Filter (MCKF) has better estimation performance as it is a single Kalman filter similar to measurement fusion technique and also it restores the flexibility and computational efficiency of state vector fusion method. A numerical example is presented wherein the derived MCKF is implemented for the attitude estimation of MAV in the 6 DOF simulation model developed in MATLAB/SIMULINK and also for a set of calibrated accelerometer and magnetometer sensor data with motor noise acquired from the autopilot mounted on the rate table of the motion simulator. It was found that MCKF exhibits substantially improved performance compared to extended Kalman filter with only accelerometer data with motor noise.

Keywords: Cascade, Kalman filters, Data fusion, Multisensor, Micro Aerial Vehicles

1. INTRODUCTION

Data fusion techniques combine data from multiple sensors to achieve greater accuracy than that could be achieved by using a single, independent sensor (James Llinas, 2008). The concept of data fusion arises from the fact that improvements in terms of classification error probability, rejection rate and interpretation robustness, can only be achieved by judicious combination of data from diverse independent sensors (Pau, 1988).

In the past few decades various Kalman filter based algorithms have been proposed for multisensor data fusion for both military and civilian applications (Hall and Llinas, 1997) (Sasiadek and Hartana, 2000) (Gan and Harris, 2001) (Sun and Deng, 2004) (Majji et al., 2007) (Olfati-Saber, 2007). These algorithms are used for fusion of internal sensors, external sensors or both. Internal sensors are those which provide the measure of physical variables of the vehicle where as the external sensors furnish the measure of the relationship between the vehicle and its environment (Sasiadek and Hartana, 2000). Some examples for fusion of internal sensors are accelerometer with magnetometer, fusion of inertial measurement unit (IMU) data with GPS data. For fusion of external with internal sensor, laser range finder with GPS forms a good example.

There are two widely used techniques for data fusion (Gan and Harris, 2001). Method I is state vector fusion - In this method there are two variants, in the first, the states are separately and parallely estimated in each sensor and then fused in a central processor to obtain an improved state estimate (Bierman and Belzer, 1985). In the second variant, the state estimated in the first sensor acts as initialized state for the second sensor and the complete sensors array work in cascade fashion. Method II is measurement fusion - This method utilizes a single Kalman filter which incorporates all the weighted or combined measurements to obtain a single state estimation. According to (Gan and Harris, 2001), performance of measurement fusion techique is better than state vector fusion. But state fusion technique is flexible and computationally efficient.

This paper, combines the advantages of both Method I and Method II. Here a modification is proposed to the traditional cascade Kalman filter. This Modified Cascade Kalman Filter (MCKF) algorithm has better estimation performance as it is a single Kalman filter similar to measurement fusion but it restores the flexibility and computational efficiency of state vector fusion. The derivation of MCKF is dealt in detail in the section 2. A numerical example is presented in section 3, where MCKF is employed for the attitude estimation of MAV. The sensors used for the fusion algorithm are accelerometer and magnetometer. In MAV, the mounting of the autopilot in close proximity to motor degrades the accelerometer data. This creates a neccesity for fusion of accelerometer data with magnetometer data. In section 4 estimation of roll and pitch in the 6 DOF simulation model of the MAV developed in MATLAB/SIMULINK is given. In section 5, experimental

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results are presented for the constant roll rate given to the rate table of a simulator with the MAV.

2. MODIFIED CASCADE KALMAN FILTER

2.1 Background

One of the widely used methodology for the fusion of data from multisensors is Cascade Kalman Filter. In this type of filter the estimated states from the first stage acts as the initialized states for the second stage. Here the complete set of Kalman filter equations are to be executed in every stage for each sensor updation. This becomes a computational burden for the on-board processor.

In the proposed MCKF prediction step and error covariance calculation are performed once; only the measurement update is executed in cascade fashion. That is, MCKF is not n-number of Kalman filters connected in cascade but it is a single Kalman filter with measurement updation from different sensors in cascade fashion.In MCKF the method of measurement updation is modified to fit in proposed framework while other structures of conventional EKF are retained.

The measurement updation for two sensor based MCKF is as follows :

$$\hat{X}^{+}_{1_K} = \hat{X}^{-}_{1_K} + K_1(Y_{1_K} - C_{1_K}\hat{X}^{-}_{1_K}) \quad (1)$$
$$\hat{X}^{+}_{2_K} = \hat{X}^{+}_{1_K} + K_2(Y_{2_K} - C_{2_K}\hat{X}^{+}_{1_K}) \quad (2)$$

Here, $\hat{X}^{-}_{1_K}$: the array of estimated states from the propagation at the instant of availability of the measurement from sensor 1. $\hat{X}^{+}_{1_K}$ and $\hat{X}^{+}_{2_K}$: the array of estimated states after the measurement updation from sensor 1 ans 2 respectively. K_1 and K_2 are the Kalman filter gains for the measurement updation 1 and 2 respectively. Y_{1_K} and Y_{2_K} : sensor measurements avaliable at the Kth instant. C_{1_K} and C_{2_K} are output matrices of measurements 1 and 2 respectively.

The block diagram of MCKF is presented in the Figure 1. For the type of measurement updation proposed, the Kalman filter gains and error covariance matrix equations are to be derived, which is discussed in the following subsections.

2.2 Error Covariance matrix of (MCKF)

Consider a system,

$$\dot{X} = f(X, U, W, t)$$

Discrete measurement model :

$$Y_{1_K} = h_{1_K}(X_K, \nu_{1_K})$$
$$Y_{2_K} = h_{2_K}(X_K, \nu_{2_K})$$

Assumption : The process and sensor noises are zero mean uncorrelated Gaussian white noises and

$$E[\nu_{1_i}\nu_{1_j}{}^T] = R_1\delta_{ij}$$
$$E[\nu_{2_i}\nu_{2_j}{}^T] = R_2\delta_{ij}$$
$$(\delta_{ij}) = \begin{pmatrix} 0....i \neq j \\ 1....i = j \end{pmatrix} \quad (3)$$

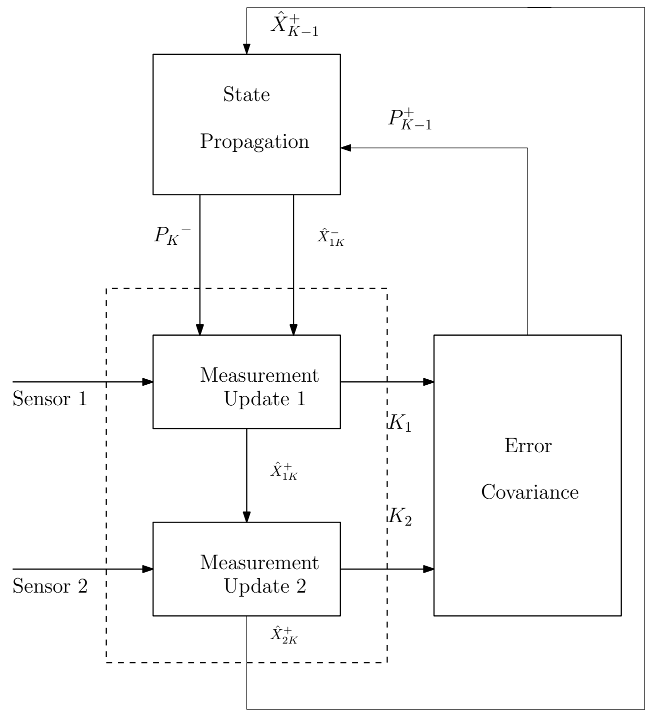

Fig. 1. Block diagram of the MCKF.

The error in estimation is given by

$$\tilde{X}^{+}_{K} = X_K - \hat{X}^{+}_{2_K} \quad (4)$$

Error covariance matrix $P_K{}^+$ is defined as the $E[\tilde{X}^{+}_{K}\tilde{X^{+}}^{T}_{K}]$. To derive the equation for $P_K{}^+$, $\tilde{X}^{+}_{K}$ is calculated as follows

$$\tilde{X}^{+}_{K} = X_K - [\hat{X}^{+}_{1_K} + K_2(Y_{2_K} - C_{2_K}\hat{X}^{+}_{1_K})] \quad (5)$$

$$\tilde{X}^{+}_{K} = X_K - [\hat{X}^{-}_{1_K} + K_1(Y_{1_K} - C_{1_K}\hat{X}^{-}_{1_K}) + K_2(Y_{2_K} - C_{2_K}\hat{X}^{+}_{1_K})] \quad (6)$$

$$\tilde{X}^{+}_{K} = (X_K - \hat{X}^{-}_{1_K}) - K_1(C_{1_K}X_K + \nu_{1_K} - C_{1_K}\hat{X}^{-}_{1_K}) - K_2(C_{2_K}X_K + \nu_{2_K} - C_{2_K}\hat{X}^{+}_{1_K}) \quad (7)$$

$$\tilde{X}^{+}_{K} = (I - K_1C_{1_K})(X_K - \hat{X}^{-}_{1_K}) - K_1\nu_{1_K} - K_2C_{2_K}(X_K - \hat{X}^{+}_{1_K}) - K_2\nu_{2_K} \quad (8)$$

substituting,

$$(X_K - \hat{X}^{+}_{1_K}) = (I - K_1C_{1_K})(X_K - \hat{X}^{-}_{1_K}) - K_1\nu_{1_K} \quad (9)$$

in the previous equation,

$$\tilde{X}^{+}_{K} = (I - K_2C_{2_K})(I - K_1C_{1_K})(X_K - \hat{X}^{-}_{1_K}) - K_1\nu_{1_K} - K_2C_{2_K}K_1\nu_{1_K} - K_2\nu_{2_K} \quad (10)$$

$$P_K{}^+ = (I - K_2C_{2_K})(I - K_1C_{1_K})P_K{}^- [(I - K_2C_{2_K})(I - K_1C_{1_K})]^T + [K_2C_{2_K}K_1]R_1[K_2C_{2_K}K_1]^T + K_1R_1K_1{}^T + K_2R_2K_2{}^T \quad (11)$$