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The adaptive Kalman filter based on fuzzy logic for inertial motion capture system

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ABSTRACT

In the inertial motion capture system, the model complexity and the large amount of computation make the completion of the orientation estimation algorithm rely solely on PC. Because the data processing speed is slow, it is difficult to realize high-speed motion tracking in the embedded system. In order to further expand the application of the motion tracking technology, this paper introduces a two-step Kalman filter, which is suitable for the embedded system. The filter is composed of two sub filters, and is adaptively adjusted based on the variance matching of fuzzy logic. IMU orientation is calculated based on the filtered acceleration vector and the estimated yaw. This approach simplifies the mathematical model, reduces the matrix operations and improves the speed of computation.

1. Introduction

As the performance of MEMS gyros and MEMS accelerometers enhances, the inertial motion capture system has been widely used, such as in autonomous navigation and gait recognition [1,2]. The typical inertia operation capture system consists of 17 to 23 IMU (Inertial/Magnetic Unit), and each IMU is comprised of 3D gyroscope, 3D accelerometer and 3D magnetometer. In the practical application, the gyro output is influenced by the zero bias, the quantization error and random noise; the accelerometer output is the sum of the gravity acceleration and linear acceleration; the magnetometer output is the sum of the geomagnetic and the disturbance magnetic field. These factors reduce the accuracy and stability of the motion capture system.

In order to improve the accuracy of the orientation estimation, variety of Kalman filters have been proposed, which mainly are divided into two types. One type is the Complementary Kalman filter. In the filter proposed by Roetenberg and Luinge [3], firstly updated the process equation with the gyro output; and then updated the measurement equation according to the difference between the estimated and the measured vector of the gravity acceleration and the geomagnetic; finally calculate orientation errors. In the filter modified by Suh, the gravity acceleration vector and the geomagnetic vector are respectively processed in two sub filters. Suh proposed an estimation equation of linear acceleration [4]. The linear accelerations in the three axes are respectively dealt with, which improves the utilization of the data. Besides, in 2006, according to the Complementary Kalman proposed by Foxlin, Bachmann used QUEST to replace Gauss–Newton iterative algorithm [5,6]. In 2011, Bachmann proposed the Complementary Kalman based on frequency [7].

The other type is the Direct Kalman filter. In the Direct filter proposed by Young, firstly update the process equation with the gyro output, then update the observation equation with the accelerometer and magnetometer output, and finally the Kalman filter gives the optical orientation estimation [8]. Bachmann modified the Direct Kalman Filter based on Gauss–Newton, which took the estimation

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values of the gravity acceleration vector and the geomagnetic vector as six dimensional error vectors, and then the error vectors were substituted into Gauss–Newton iterative algorithm to get the orientation estimation error of IMU, finally to correct the process vector [9]. In the Direct Kalman filter proposed by Lee, the orientation and the extra acceleration could be accurately estimated [10,11]. In addition, in the Direct filter proposed by Angelo M.Sabatini, bias compensation of the sensors can control the influence on orientation brought by body motion and magnetic disturbance [12].

The models of the two filters are mature, but involve a large number of operations, which makes them achieve high-speed data processing only on PC. In order to avoid the dependence on PC, this paper introduces a two-step Kalman filter [13]. It divides the typical Kalman filter into two sub Kalman filters, and separately deals with the gravity acceleration vector and the geomagnetic vector. The new algorithm simplifies the model of the IMU, reduces the amount of computation, and meets the requirement of embedded systems. Meanwhile, the inaccuracy of the noise statistical properties largely affects the estimation of the Kalman filter, and even leads to filter divergence. To solve this problem, this paper introduces the adaptive adjustment method based on fuzzy logic [14,15], which can further improve the estimation accuracy.

2. The error model of sensor

Assume y_a is the accelerometer output; $C(q)g$ is the gravity acceleration vector in body frame, $a_{b,t}$ is the linear acceleration; $w_{a,t}$ is the white noise of the linear acceleration; v_a is the white noise of the accelerometer output, and the mean value of v_a is zero. The accelerometer signals are described in Eq. (1).

$$y_a - a_{b,t} = C(q)g + v_a + w_{a,t} \tag{1}$$

Assume y_m is the magnetometer output; $C(q)m$ is geomagnetic field vector in body frame; d_t is the disturbance magnetic; v_m is the white noise of the magnetometer output and the mean of v_m is zero. The magnetometer signals are described in Eq. (2).

$$y_m = C(q)m + d_t + v_m \tag{2}$$

The magnetic disturbance d_t is modeled by the following Markov scheme, described in Eq. (3) [3].

$$d_t = c_d d_{t-1} + w_{d,t} \tag{3}$$

Assume y_g is the gyro output; ω is angular velocity in body frame; $b_{g,t}$ is the offset; v_g is the white noise of the gyro output and the mean of v_g is zero. The gyro signals are described in Eq. (4).

$$y_g = \omega + b_{g,t} + v_g \tag{4}$$

And the offset $b_{g,t}$ is modeled as a first order Markov process, driven by the white noise $w_{g,t}$, shown in Eq. (5) [3].

$$b_{g,t} = b_{g,t-1} + w_{g,t} \tag{5}$$

3. The two-step Kalman filter

The proposed two-step Kalman filter consists of two sub filters, as shown in Fig. 1. The first Kalman filter is to estimate the gravity acceleration vector in the body frame. The second Kalman filter is to estimate yaw. To the first filter, update the IMU orientation according to the gyro output; then estimate the gravity acceleration vector as the process vector of the Kalman filter; the measurement vector is the corrected output of the accelerometer; at last calculate pitch and roll according to the filtered gravity acceleration vector. Then pitch and roll are substituted to the geomagnetic field equation to obtain the computed yaw. The computed yaw is as the measurement vector of the second Kalman filter. The process vector of the second Kalman filter is the updated yaw from the gyro output. The optimal estimation of yaw can be obtained after the second Kalman filter acts.

3.1. The IMU orientation updating

Assume the inertial frame of the IMU is p_n, and the body frame is p_b. In the Euler angles, the conversion equation between different frames is shown in Eq. (6):

$$p_b = \begin{bmatrix} \cos\theta\cos\psi & \cos\theta\sin\psi & -\sin\theta \\ -\cos\phi\sin\psi + \sin\phi\sin\theta\cos\psi & \cos\phi\cos\psi + \sin\phi\sin\theta\sin\psi & \sin\phi\cos\theta \\ \sin\phi\sin\psi + \cos\phi\sin\theta\cos\psi & -\sin\phi\cos\psi + \cos\phi\sin\theta\sin\psi & \cos\phi\cos\theta \end{bmatrix} p_n$$

where ϕ is pitch, ψ is yaw and θ is roll.

$$\text{Let}\quad C_n^b = \begin{bmatrix} \cos\theta\cos\psi & \cos\theta\sin\psi & -\sin\theta \\ -\cos\phi\sin\psi + \sin\phi\sin\theta\cos\psi & \cos\phi\cos\psi + \sin\phi\sin\theta\sin\psi & \sin\phi\cos\theta \\ \sin\phi\sin\psi + \cos\phi\sin\theta\cos\psi & -\sin\phi\cos\psi + \cos\phi\sin\theta\sin\psi & \cos\phi\cos\theta \end{bmatrix}$$

Thus, we have

$$P_b = C_n^b p_n \tag{6}$$