Human Motion Tracking based on Complementary Kalman Filter *

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***Abstract*—Miniaturized Inertial Measurement Unit (IMU) has been widely used in many motion capturing applications. In order to overcome stability and noise problems of IMU, a lot of efforts have been made to develop appropriate data fusion method to obtain reliable orientation estimation from IMU data. This article presents a method which models the errors of orientation, gyroscope bias and magnetic disturbance, and compensate the errors of state variables with complementary Kalman filter in a body motion capture system. Experimental results have shown that the proposed method significantly reduces the accumulative orientation estimation errors.**

I. Introduction

Orientation estimation is essential for various kinds of applications, such as unmanned micro-aerial vehicles, robotics, human motion analysis and mobile devices [1-4]. For human motion capture and analysis, inertial sensors have incomparable superiority than other sensing technologies. However, obtaining orientation by using gyros is only accurate for a short time because of its inherent noise and drift with time. To reduce the drifts and cumulative errors, many laboratories are dedicated in the past few decades. Now, it's a common way to use gyroscope with accelerometer and magnetometer [5-6].

Many filter models have been proposed to develop the most appropriate solution to fuse the data of three sensors. *Han and Wang* proposed a linear system error model based on the Euler angles [7]. *Sabatelli, et al.* presented an extended Kalman filter to calculate the attitude angles and the heading angles respectively [8]. *Shengzhi Zhang, et al.* described a dual-linear Kalman filter. They defined gravity and geomagnetic field as two state vectors and divided them into two independent linear filters and updated separately [9]. *Daniel, et al.* used a complementary Kalman filter to compensate the magnetic disturbances and estimate single sensor module orientation [10]. *Xuebing Yuan, et al.* adopted a quaternion-based unscented Kalman filter (UKF) algorithm to obtain the high-accuracy indoor heading estimation [11]. However, these systems have some common limitations. Firstly, the measurements are chosen based on the disturbance of accelerations and magnetic fields, which may cause the lost of useful information. Secondly, too many trigonometric functions and Taylor expansions increase the computation and slows the rate of iteration. Thirdly, the inherent noise and drift are accumulated with time quickly.

We propose a new orientation estimation method in this paper. This method models the errors of orientation, gyroscope bias and magnetic disturbance, and compensate the errors of state variables with complementary Kalman filter (CKF) in the inertial navigation system. Forward kinematics are combined to realize the orientation tracking of whole body and drive the 3D human model in real time. This approach has a remarkable modification as the measurements collected by magnetometer and accelerometer are fully used. On account of the errors of state variables being updated with time, accumulative errors won't be generated between adjacent time, which contributes to long-time movements estimation. Besides, state transfer matrix equals zero all the time which will reduce the computational complexity.

The paper is organized as follows: Section 2 describes the human model briefly and introduces the complementary Kalman filter algorithm. Section 3 gives tests of two different movement scenarios, and analyzes the results comparing the proposed method and the multiple adaptive fusion.

II. Model Algorithm

A. Human Model

A 3D human skeleton model is built to obtain accurate orientation estimation in real-time, which fits to the human body anatomic and biological character. Positions are analyzed using forward kinematics [12]. To describe the rotation of joints and skeletons in the space, it's essential to define four coordinate systems: Global Coordinate System, Body Coordinate System, Sensor Coordinate System and Model Coordinate System. To meet the rotation relationship between every coordinate system, we filter the appropriate means of mathematics. Quaternion can avoid the singularity problem in Euler angle, and the complex matrix operations in Direction Cosine Matrix [13-14]. Therefore, we choose quaternion to express the rotation relationship.

B. Complementary Kalman Filter Model

Complementary Kalman filter is used in the inertial navigation system. It bases on a model of errors and adopts a feedback mechanism to compensate the errors of state variables. For every segment in a systemic frame, the error state vector can be defined as $x_t= [\delta\theta_t, \delta b_t, \delta d_t]^T$, which represents the orientation error, the gyroscope offset and the error in magnetic disturbance. Every error state variable has three elements, which constitutes a nine-dimensional vector. The flow chart in Fig. 1 describes the fusion of the three sensors in the error model for combined inertial and magnetic orientation sensing.

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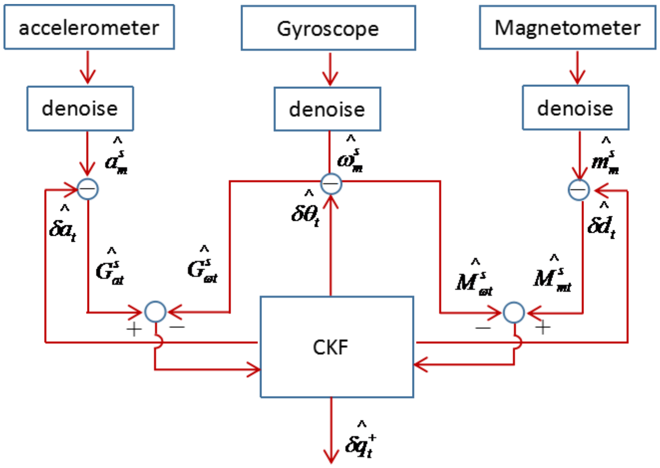

Figure1. The CKF flow chart for orientation estimation

The error state dynamic presentation are as follows:

$$x_{t+1} = A_t x_t + w_t \quad (1)$$

The measurement equation describes the relation between the state vector x_t and the measured variable z_t by H_t:

$$z_t = H_t x_t + n_t \quad (2)$$

w_t and n_t are two random variables which represent the system and the measurement noise respectively, which are assumed mutually independent with normal distribution and white power spectrum. Q_{wt} and Q_{nt} represent their covariance matrices respectively.

Note that the state variables at current time are only affected by the system noise. Therefore, the A matrix is a zero matrix. It's also consistent with CKF significance, which reduces the computational complexity in system iteration. After updating the error states via CKF, the orientation estimation is compensated in order to rectify the prediction at t time before. We can also describe it in quaternion form [1]:

$$q_t = \hat{q}_t \otimes \delta\hat{q}_t^+ \quad (3)$$

After providing the error state information, the error of the orientation will be set to zero. As the gyroscope offset and the error in the magnetic disturbance follow the first order Markov process, they will be updated over time.

We define $\hat{x}_t^-$ as the prior state estimation for x_t in the case of knowing the state vectors before time t, and $\hat{x}_t^+$ as the posterior state estimation after updating based on the measurement z_t at time t. $\hat{x}_t^+$ is updated according to:

$$\hat{x}_t^+ = \hat{x}_t^- + K_t\left(z_t - H_t \hat{x}_t^-\right) \quad (4)$$

In the recursive formula of Kalman filtering, K_t is the Kalman gain matrix which minimizes the posteriori estimated error covariance matrix:

$$K_t = P_t^- H_t^T \left(H_t P_t^- H_t^T - Q_{nt}\right)^{-1} \quad (5)$$

P_t is updated according to the Ricatti equation:

$$P_t^- = A_{t-1} P_{t-1} A_{t-1}^T + Q_{wt} \quad (6)$$

State matrix H_t and measurement noise n_t can be obtained by considering the effect of the gyroscope offset, orientation error, and magnetic disturbance. The inclination is defined as the estimation value on the vertical direction and the magnetic vector is defined on the horizontal direction. As each orientation is decomposed into horizontal and vertical vectors, these three state variables are updated when inclination and magnetic vector are treated as two inputs for complementary Kalman filter.

C. Error Propagation

In this paper, we employ inclination estimates from gyroscope and accelerometer. The measurement difference vector on the z-axis of the global coordinate system is formed by the difference between the gyroscope and accelerometer inclination estimates. Two relevant factors causing an inclination error are orientation error and gyroscope offset error. The inclination difference can be expressed as:

$$z_{it} = \hat{G}_{\omega t}^{s} - \hat{G}_{at}^{s} \quad (7)$$

$\hat{G}_{\omega t}^{s}$ and $\hat{G}_{at}^{s}$ are the inclination based on the gyroscope signal and the accelerometer signal in the sensor coordinate frame, respectively.

The gravity vector affects the inclination estimate from the accelerometer. Therefore, we abstract it from accelerometer measurement a_m^s by subtracting the predicted acceleration $\hat{a}_t^{s-}$ and normalize it to obtain the estimation of the inclination:

$$\hat{G}_{at}^{s-} = \frac{a_m^s - \hat{a}_t^{s-}}{\left|a_m^s - \hat{a}_t^{s-}\right|} \quad (8)$$

For the inclination estimate from the gyroscope, the orientation is found as the strapdown integration can be approximated with [15], where T is the sample time and $\hat{\omega}_t^{s}$ is the angular velocity estimates:

$$\hat{G}_{\omega t}^{s-} = \hat{G}_{t-1}^{s+} - T \cdot \hat{\omega}_t^{s} \times \hat{G}_{t-1}^{s+} \quad (9)$$

The global magnetic vector is estimated by comparing the difference between the magnetic field vector estimation from gyroscope and magnetometer. It implies the high accuracy measured by sensors when the difference is small. The magnetic field vector difference can be expressed as:

$$z_{mt} = \hat{M}_{mt}^{s} - \hat{M}_{\omega t}^{s} \quad (10)$$

$\hat{M}_{\omega t}^{s}$ and $\hat{M}_{mt}^{s}$ are the estimates of the magnetic field vector based on gyroscope signal and magnetometer signal in the sensor coordinate frame respectively.

The estimate of $\hat{M}_{mt}^{s-}$ is the measured magnetic vector m_m^s subtracted by the estimated magnetic disturbance vector $\hat{d}_t^{s-}$:

$$\hat{M}_{mt}^{s-} = m_m^s - \hat{d}_t^{s-} \quad (11)$$

The magnetic vector based on gyroscope is described similarly as (9):

$$\hat{M}_{\omega t}^{s-} = \hat{M}_{t-1}^{s+} - T \cdot \hat{\omega}_t^{s} \times \hat{M}_{t-1}^{s+} \quad (12)$$

Now, the measurement equation is expressed as:

$$z_t = \begin{bmatrix} \hat{G}^s_{\omega t} - \hat{G}^s_{at} \\ \hat{M}^s_{\omega t} - \hat{M}^s_{mt} \end{bmatrix} = H_t \cdot \left[\delta\theta_t \quad \delta b_t \quad \delta d_t\right]^T + n_t \tag{13}$$

Matrix H_t and the noise n_t can be determined as:

$$H_t = \begin{Bmatrix} \left[\left(-\hat{G}^s_t - \hat{a}^{s-}_t\right)\times\right] & \left[T \cdot \hat{G}^s_t \times\right] & 0_3 \\ \left[\left(-\hat{M}^s_t - \hat{d}^{s-}_t\right)\times\right] & \left[T \cdot \hat{M}^s_t \times\right] & -K_d \cdot I_3 \end{Bmatrix} \tag{14}$$

$$n_t = \begin{Bmatrix} \frac{1}{g}\left(-K_a \cdot \delta a^{s+}_{t-1} + n_{at} + w_{at}\right) - \hat{G}^s_t \times T \cdot n_{\omega t} \\ w_{dt} + n_{dt} - \hat{M}^s_t \times T \cdot n_{\omega t} \end{Bmatrix} \tag{15}$$

The error covariance matrix of the system noise term can be obtained with a premise that the matrix A equals the zero matrix and by taking the variances of the error propagations:

$$Q_{wt} = \begin{bmatrix} Q^+_{\theta,t-1} + T^2 \cdot Q^+_{b,t-1} + T^2 \cdot Q_{\omega t} & T^2 \cdot Q^+_{b,t-1} & 0 \\ T^2 \cdot Q^+_{b,t-1} & Q^+_{b,t-1} + Q_{wb} & 0 \\ 0 & 0 & K_d^2 \cdot Q^+_{d,t-1} + Q_{wd} \end{bmatrix} \tag{16}$$

The measurement noise covariance was found by taking the covariance of (15):

$$Q_{nt} = \begin{Bmatrix} \frac{1}{g}\left(K_a^2 \cdot Q^+_{a,t-1} + Q_{wat} + Q_{nat}\right) + Q_{n\omega wt} \\ Q_{wdt} + Q_{ndt} + Q_{n\omega t} \end{Bmatrix} \tag{17}$$

where Q_a, Q_b, Q_θ and Q_d are the error covariance matrices of acceleration, offset, orientation and magnetic disturbance. Q_{vA}, Q_{vG} and Q_{vM} are the covariances of the measurement noise term of accelerometer, gyroscope and magnetic disturbance. w_{at}, w_{bt} and w_{dt} are the offset noise, the driving Gaussian noise of magnetic disturbance, and Q_{wa}, Q_{wb} and Q_{wd} are the covariance matrix of them.

III. EXPERIMENTAL RESULT

A. Experimental Setting

The objective of the experiment is to compare CKF with UKF with optical motion capture Vicon as reference. Micro-sensor motion capture system（MMocap）is designed and developed by our laboratory, which consists of 16 IMUs and uses unscented Kalman filter(UKF) for orientation estimation [16]. Vicon uses 11 high speed cameras to track 65 marks on body. During the experiments, performer wears both 16 IMUs and 65 markers on his body, as shown in Fig. 2(a). Both of the sampling frequency are 100Hz. Raw sensor data are processed by both UKF and CKF to produce orientation estimation results. To assess the accuracy and stability of CKF and UKF, Root Mean Squares (RMS) is calculated between the filter estimation and the reference over samples.

B. Experimental Results

In the first experiment, performer squats and rises twice, as shown in Fig. 2(b). Fig. 3(a) shows raw measurements of this movement. Fig. 3(b-d) illustrate the results comparing the proposed algorithm and UKF with the reference orientation provided by optical system. Table Ⅰ gives the comparison on RMSE of two fusion methods. As the motion is focused on lower body, we take right upper thigh as an example to analyze.

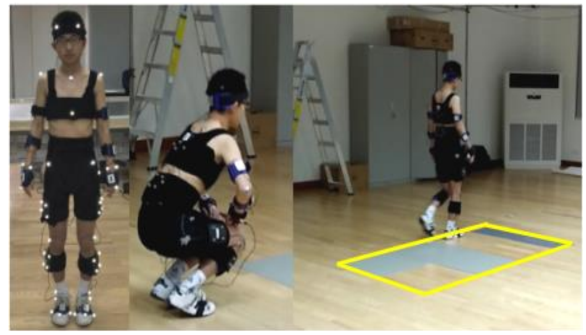

Figure2. (a) Performer puts on the suit with sensors and attaches 65 markers; (b) Squatting and rising experiment; (c) Walking motion experiment

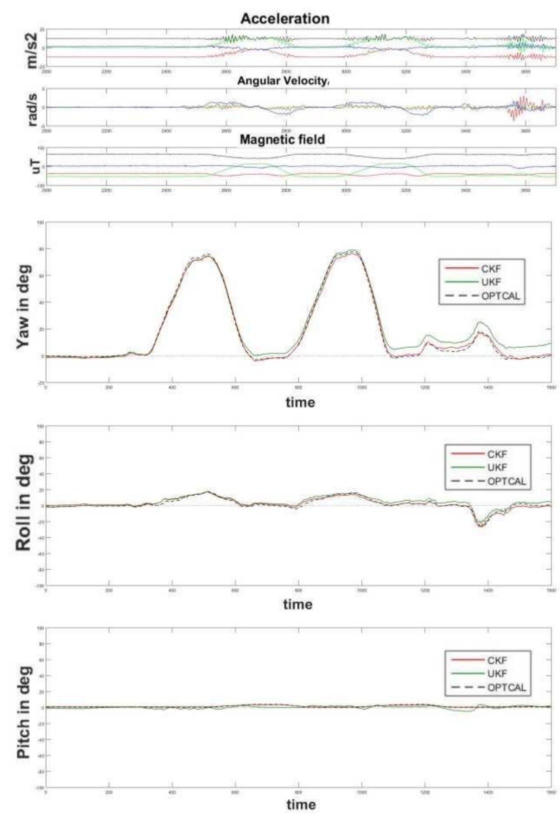

Figure3. The result of first experiment: (a) Raw data; (b)Yaw angle; (c)Roll angle; (d) Pitch angle

As illustrated in Fig. (3) and Table Ⅰ, the sensor module is rotated along the z-axis during the squatting and rising, which causes a significant angular variation in yaw. The RMSE in yaw by CKF is 1.2609° (peak error 4.0537°), while 4.5839° (peak error 9.7860°) by UKF. In addition, upper thigh extends in space when performer squats, changing the angle in Roll and Pitch slightly. It can be seen that the RMSE in pitch and roll by CKF is 1.4824° (peak error 1.6648°) and 2.6716° (peak error 5.5647°), showing that a more reasonably accurate result than by UKF. As we can see from Fig. (3), the margin fluctuation of position estimated by UKF is much bigger than CKF, owing to choosing appropriate model for data fusion in real-time. The result shows that CKF curve is smoother than UKF and matches the reference value better.

After the rotation, the estimation in yaw angle is much closer to zero by CKF, which is about 0.4°, and the error by UKF is up to 8.9°.

TABLE I. COMPARISON ON RMS ERRORS OF SIMPLE MOTION

Filter	Squatting and Rising Experiment		
	RMSE in Pitch	***RMSE in Roll***	***RMSE in Yaw***
CKF	1.4824°	2.6716°	1.2609°
UKF	2.0614°	2.8128°	4.5839°

In the second experiment, performer walks with a rotation of 90° to the right three times along the route lining out in yellow, as shown in Fig. 2(c). We repeat this experiment six times. Each time the performance lasts 35s. Fig. 4(a) shows the accelerations, angular rates and magnetic field strengths calculated by one single sensor. Fig. 4(b-d) illustrates the comparison of Euler angle resulted in different methods after processing the original data with the reference orientation provided by optical system. Table Ⅱ gives the comparison on RMSE of two fusion methods. Also, we take left upper thigh as an example to analyze.

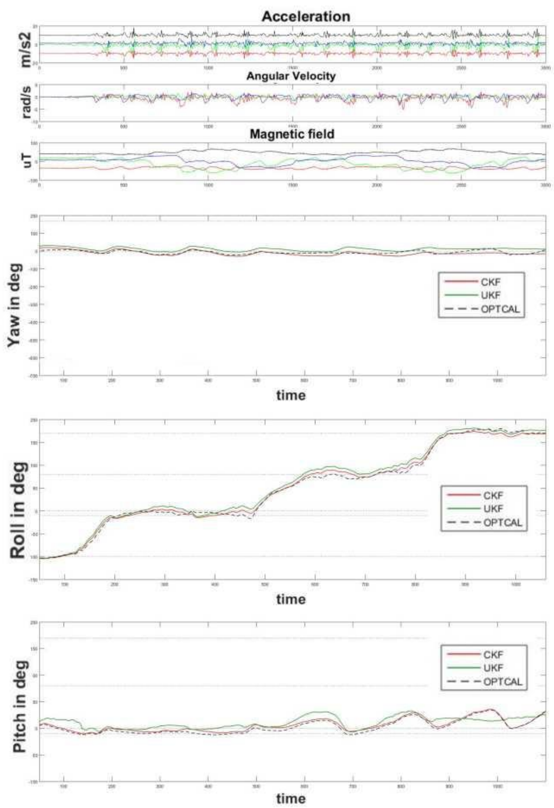

Figure4. The result of walking and rotating experiment: (a) Raw data; (b)Yaw angle; (c)Roll angle; (d) Pitch angle

During the rotation, the sensor module is rotated along the x-axis, which causes a significant angular variation in Roll. After three times rotation, the angle is approximately reached 270°. According to Table Ⅱ, a significant angle offset shows by UKF algorithm with time. The RMSE in yaw and pitch are 6.8862° and 7.3137° respectively. To the contrary, it shows smaller errors in CKF, namely 1.6392° and 1.9784°. It indicates that, with the increasing duration of movement, the accumulative errors affect the UKF estimation result. As a consequence, CKF has a better stability than UKF and reduces the accumulative error significantly.

TABLE II. COMPARISON ON RMS ERRORS OF WALKING MOTION

Filter	Walking and Rotating Experiment		
	RMSE in Pitch	***RMSE in Roll***	***RMSE in Yaw***
CKF	1.9784°	3.8443°	1.6392°
UKF	7.3137°	4.8661°	6.8862°

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