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Extended Abstract

Construction of a Kalman filter for real time motion measurement

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Abstract

Small and light-weight 9-axis sensor modules have been developed with the MEMS technology progresses. The Kalman filter is often used for the offline pose estimation by utilizing the measurement information after the 9-axis sensor modules measured human motion. The offline process, nevertheless, takes a while for the pose estimation. This study proposed a Kalman filter that allowed real-time pose estimation using a noise covariance matrix based on the 9-axis sensor module output. The proposed method result was generally consistent with the result obtained from the optical motion capture system.

Keywords

Kalman filter, Noise covariance, Pose estimation, Real-time, 9-axis sensor module

1. Introduction

Small and light-weight 9-axis sensor modules have been developed with the MEMS technology progresses. 9-axis sensor modules have been used for pose estimation in a wide range of fields such as medical welfare, sports, and entertainment [1]. The Kalman filter is often used for pose estimation using 9-axis sensor modules because of its low computational load and excellent noise resistance [2]. However, it is not easy to determine the noise covariance in the Kalman filter by accurately detecting the dynamic characteristic of the measurement target and the noise characteristics of a 9-axis sensor module. The Kalman filter is often used for the offline pose estimation by utilizing the measurement information after the 9-axis sensor modules measured human motion. The offline process, nevertheless, takes a while for the pose estimation. Applying the Kalman filter for the real-time pose estimation in clinical practice requires determining the noise covariance in real-time to increase the estimation accuracy.

Therefore, in this study, we constructed a Kalman filter that could be used for accurate pose estimation in real time utilizing the noise covariance matrix based on the 9-axis sensor module outputs. The pitch angle estimation was performed in this study, as the first step of real time 3D pose estimation.

2. Method

2.1 Initial pitch angle

The initial pitch angle was calculated from Eq. (1) using the acceleration sensor output at rest [3].

$$\theta_A = atan2\frac{-A_x}{\sqrt{A^2{}_y+A^2{}_z}} \tag{1}$$

where A_x , A_y and A_z are the accelerometer output for x, y, and z axes, respectively

2.2 Kalman filter algorithm using noise covariance based on sensor output

A linear Kalman filter for pitch angle estimation was constructed. The state and observation equations are shown in Eqs. (2) and (3), respectively.

$$x_{t+1} = Ax_t + Bu_t + w_t \tag{2}$$

$$y_t = Cx_t + v_t \tag{3}$$

$$x_t = [\theta_t], y_t = \left[atan2\frac{-A_{x,t}}{\sqrt{A_{y,t}{}^2 + A_{z,t}{}^2}} \right]$$

where x_t is the pitch angle, u_t is the gyro sensor output, w_t is the process noise, v_t is the observation noise, and A=B=C=1. Then, the prediction step (Eqs. (4) and (5)) and the filtering step (Eqs. (6), (7), and (8)) were calculated using the linear discrete-time system represented by Eqs. (2) and (3).

$$x_{t+1}^{-} = Ax_t + Bu_t \tag{4}$$

$$P_{t+1}^{-} = AP_tA^T + BQ_tB^T \tag{5}$$

$$K_{t+1} = P_{t+1}^{-}C^T(CP_{t+1}^{-}C^T + R_t)^{-1} \tag{6}$$

$$x_{t+1} = x_{t+1}^{-} + K_{t+1}(y_{t+1} - Cx_{t+1}^{-}) \tag{7}$$

$$P_{t+1} = (I - K_{t+1}C)P_{t+1}^{-} \tag{8}$$

where P represents the error covariance matrix, K denotes the Kalman gain, and Q and R respectively denote the covariance matrices of the process noise and observation noise. Q and R are based on the gyro sensor output and accelerometer output, respectively, as shown in Eqs. (9) and (10).

$$Q_t = 0.0001\sqrt{{\omega_{x,t}}^2 + {\omega_{y,t}}^2 + {\omega_{z,t}}^2} \tag{9}$$

$$R_t = 0.0001\sqrt{{A_{y,t}}^2 + {A_{z,t}}^2} \tag{10}$$

where $\omega_{x,t}$, $\omega_{y,t}$, $\omega_{z,t}$ respectively stand for the gyroscope output for x, y *and* z axes. A_y and A_z respectively express the accelerometer outputs for the y and z axes.

3. Experiment

The 9-axis sensor module used in this study (BMX055 from Bosch) includes a three-axis gyro sensor, a three-axis acceleration sensor, and a three-axis geomagnetic sensor. The experiments were conducted with the measurement range of ±2 G for the acceleration sensor and ±1000 degree/sec for the gyro sensor. The size of the sensor is 14 x 10 x 5 mm and the weights 5 g. The microcontroller board used in the experiment was STM32F401RE. Measurement data acquisition and setting for the 9-axis sensor module was performed through I2C communication. The maximum communication speed of the I2C communication was set to 400 kbps. The 9-axis sensor module was attached to a two-link mechanism controlled by a servomotor. The mechanism moved in a range of 90 degrees from the initial posture of 0 degree.

4. Result

The results are shown in Fig. 1. The horizontal axis is the normalized time from starting the operation of the robot to the end of that as 100%.

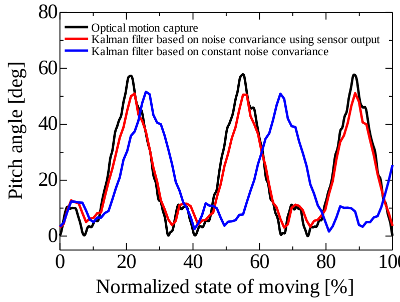

Fig.1. Measurement results

The vertical axes are the pitch angle results. The black solid line represents the result obtained from the optical motion capture system, which is used as the true value in the experiment. The red solid line represents the result obtained from the Kalman filter using the proposed method. The blue solid line shows the result from the Kalman filter, which used the constant process and observation noise covariances. The constant process and observation noise covariances were determined to maximize the log-likelihood using 100 sample data before the measurement. The proposed method result is generally consistent with the result obtained from the optical motion capture system. On one hand, the result using the constant process and observation noise covariances show a time-delay result.

5. Conclusion

The proposed method could estimate the pitch angle in real time utilizing the noise covariance matrix based on the 9-axis sensor module outputs. The method is expected to be useful for estimating motion in sports and healthcare applications.

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