Sensor Fusion using kalman filter

Lab report

submitted by

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0.1 INTRODUCRTION

Attitude estimation is often inaccurate during highly dynamic motion due to external acceleration. In this report we discuss Kalman filter-based attitude estimation using a algorithm to overcome external acceleration. This algorithm is based on an external acceleration compensation model to be used as a modifying parameter in adjusting the measurement noise covariance matrix of the Kalman filter.The inertial measurement unit (IMU) is typically used to determine the attitude, that is, roll and pitch, by fusing accelerometer and gyro data. The most notable disturbance of attitude determination is external acceleration , which is caused by a change of velocity in magnitude or direction. The attitude solution provided by the gyro is prone to being unbounded, to bias, and to random-walk errors. In static or slow movement, the accelerometer measures roll and pitch by leveling to correct the gyro-unbounded error. This is due to the trustworthiness of the gravitational measurement. Therefore, a proper fusion of IMU data and the algorithm to compensate for external acceleration is needed to overcome the shortcomings of each sensor and the effect of external acceleration.

0.2 Algorithm and equation

Process and Measurement Models:- We initially defined the states and the observation variables for the system model. We set attitude and gyro bias as state variables, since the bias errors are a highly complex function to the ambient temperature. The Euler angle was the angle representation.The state variable x(t) and the measurement variable z(t) are defined as follows:

$$x = [\phi \quad \theta \quad \psi \quad b_x \quad b_y \quad b_z]^T \tag{1}$$

$$x = [\phi_a \quad \theta_a \quad \psi_a]^T \tag{2}$$

where ϕ (roll) and θ (pitch) are the rotation angles about the x- and y-axes and ψ is yaw angle, but it is not of concern in this study. These come from the integration of the rate of change from gyros, while b_x, b_y, and b_z are biases from gyro in x-, y-, and z-axis, respectively. We use the measurement from the accelerometer in order to calculate ϕ_a, θ_a, and ψ_a as measurement variables. The system equation is given by

$$\dot{x(t)} = f(x(t)) + w(t) \tag{3}$$

$$z(t) = Hx(t) + v(t) \tag{4}$$

where f(x(t)) is a nonlinear function representing the relation between gyros data and kinematic equation for the Euler angles $(X \rightarrow Y \rightarrow Z)$; H is state to measurement matrix, and w(t) and v(t) are process noise and measurement noise, respectively, which are assumed to be uncorrelated Gaussian distributed white noise.

Steps of kalman filter algorithm is:-

- Set the initial values for states and error covariance

$$\widehat{x}_0, P_0 \tag{5}$$

- Predict states and error covariance

$$\widehat{x}_k^- = f(\widehat{x}_{k-1}) \tag{6}$$

$$P_K^- = A_k P_{k-1} A_k^T + Q \tag{7}$$

- Compute the Kalman gain

$$K_K = P_k^- C_k^T (C_k P_K^- C_k^T + Q)^{-1} \tag{8}$$

- Compute the states estimate

$$\hat{x} = \hat{x}^- + K_k(z_k - H\widehat{x}_k^-) \tag{9}$$

- Compute the error covariance

$$P_K = (I - K_k C_k) P_k^- \tag{10}$$

Figure 1 shows the structure of the proposed algorithm combined with the extended Kalman filter algorithm. The notations and meanings of , $\widehat{x}_k$, $\widehat{x}_k^-$, P_K, and P_K^- are estimates of state, prediction of state, estimate of the error covariance, and the prediction of the error covariance, respectively

0.3 Conclusion

In this report, we tried to implement the sensor fusion using Kalman filter. With the help of this report, we came to know about the derivations involving the use of Kalman filter and finally, with experiment 3 we got to know how sensor fusion is done and is a critical step of the experiment.

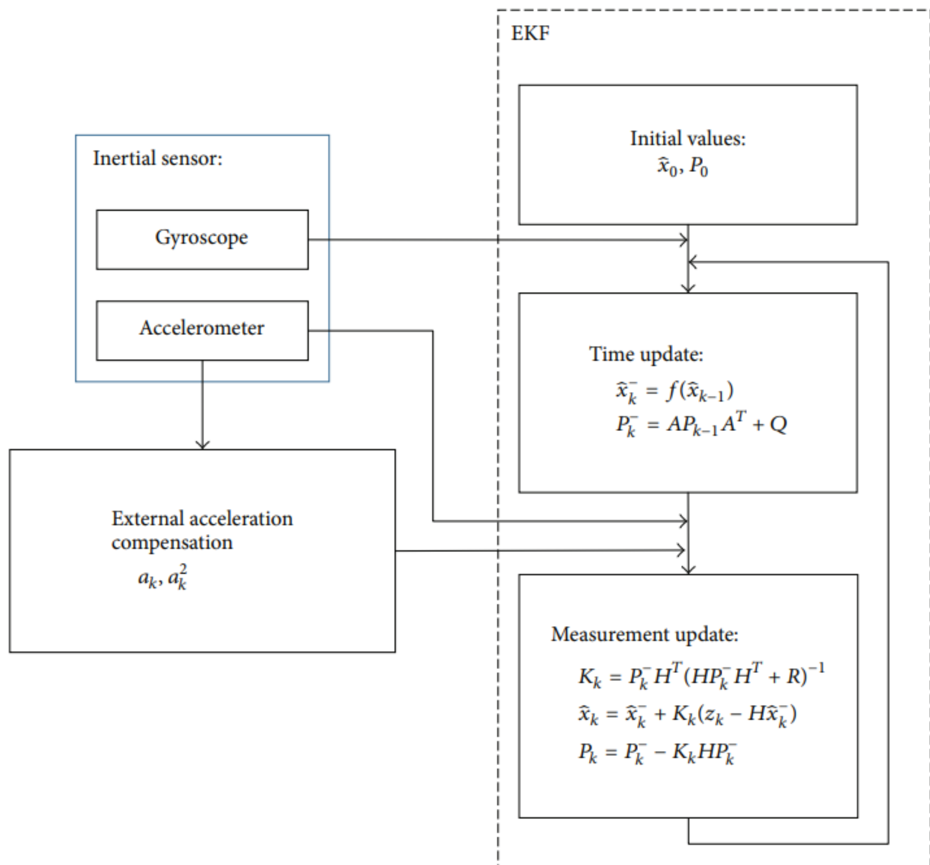

Figure 1: Structure of Algorithm