A Novel Motion-Capture System:

Using the Kalman Filter to Fuse Inertial Sensor Data

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Abstract: This project used an accelerometer and gyroscope to estimate the orientation of the arm. The orientation of the forearm and upper arm are estimated using the Kalman Filter, which can fuse the sensors' data together. The joint constraint provided by the elbow is used to increase the accuracy of the estimation. In the end, the pitch and roll angle estimates are accurate, while the yaw angle estimate becomes increasingly inaccurate over time.

Introduction

Human motion-capture systems have many applications. Biomedical and sports researchers use motion-capture to analyze how the body moves. Motion-capture is also used in movies, tv shows, and video games to record human movement for animation. Most motion-capture systems use cameras, but these systems have limitations as cameras need good lighting to work. This project attempts to create a inertial motion-capture system using accelerometers and gyroscopes and the Kalman filter to estimate the orientation of the arm. In this project, a orientation estimate of the forearm is first made with the accelerometer. Then the gyroscope data is incorporated for a more accurate estimate. Finally, an accelerometer and gyroscope are used to also find the orientation of the upper arm, and the joint constraint provided by the elbow makes a more accurate estimation of the orientation of the arm.

Design Plan

This project uses a Raspberry Pi and 2 MPU-6050s to estimate the orientation of the arm. The MPU-6050 has both an accelerometer and gyroscope and interfaces with the Raspberry Pi using the I2C protocol.

Kalman Filter

The Kalman Filter is a mathematical algorithm that can estimate a state given noisy measurement data and past estimates of that state. Given a state vector, the Kalman Filter models this state's change as some random process that changes given the measurement data. In this project, the Kalman Filter is used once to make an orientation estimate with the accelerometer, and again to fuse the accelerometer and gyroscope data to create an estimation.

The Kalman Filter models a state, x, as a combination of its past state, an outside control input, u, and process noise w.

$$\mathrm{x}_t = \mathrm{Ax}_{t-1} + \mathrm{Bu}_{t-1} + \mathrm{w}_t$$

The filter models the measurement vector as a combination of the state and measurement noise.

$$z_t = Hx_t + v_t$$

The Kalman filter has a two step process to estimate a state. First, in the time update, the filter makes a preliminary estimate using the previous estimate and the control input. The error covariance matrix, P, is also estimated. Next, in the measurement update, the filter compares the preliminary estimate to the measurement vector to create the final estimate. For this, a gain matrix, K, is calculated to update the state vector in a way that would minimize the error covariance matrix.

Accelerometer

Using just the accelerometer, we can estimate the pitch and roll orientation angles of the forearm body segment (pitch represents the rotation around the y-axis, and roll represents the rotation around the x-axis). To do this, the Kalman filter is used to estimate the direction of gravity relative to the sensor's frame of reference. In the global frame of reference, the gravity vector is always pointing down, in the -z direction. But the direction of the gravity vector in terms of the axes of the sensor is not always in the -z direction. By finding the gravity vector in terms of the sensor frame axes, the pitch and roll angles can be estimated. The yaw orientation angle, the rotation around the z-axis, cannot be determined from the accelerometer because as the body segment's yaw angle changes, the direction of gravity in the sensor frame does not.

The accelerometer signal vector, y, is a 3x1 vector that represents the accelerometer's x, y, and z measurements. It is composed of the acceleration vector a, gravity vector g, offset vector b, and measurement noise v.

$$y_t = a_t + b_t - g_t + v_t$$

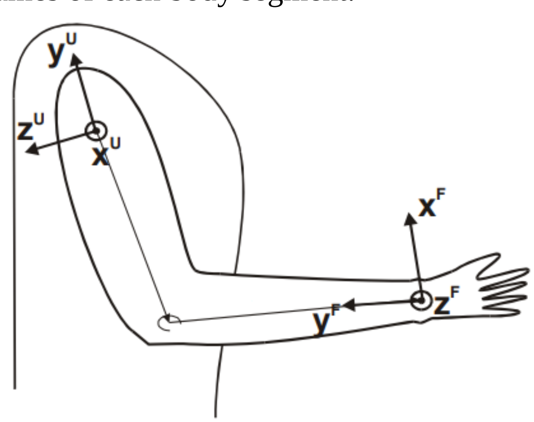
The three components of the accelerometer signal must be estimated using the Kalman Filter. First, for the time update, a preliminary estimate is made by taking past estimates of the components and rotating them. The angular velocity of the body segment can be approximated using the Small Angle approximation with the accelerometer signal vector. The angular velocity approximation can be used to rotate the previous component estimations to find the preliminary estimations. Then, the Kalman Filter's measurement update can be used to find the final estimate of the accelerations, gravity, and offset. The estimate of the gravity vector is in terms of the sensor frame, so using trigonometry the pitch and roll angles can be estimated.

Gyroscope

The gyroscope is used to provide complement the accelerometer orientation estimation by providing more accurate pitch and roll angle estimation while also creating a yaw angle estimation. A Kalman Filter is again used for the fusion of these sensors. In this instance of the filter, the state that we are measuring is the orientation angles and the gyroscope offset. The gyroscope output is not the measurement vector, in this case the control input, u, is the gyroscope output. The measurement vector, z, in this case is the orientation estimate from the accelerometer. What this does is make a preliminary estimate only using the gyroscope. Then, in the filter's measurement step, use the accelerometer orientation estimate as a reference. This creates a more accurate pitch and roll angle estimate. The yaw angle estimate is not as accurate as because it relies only on the gyroscope.

Joint Constraint

Once the orientation of the forearm is estimated using an accelerometer and a gyroscope, the orientation of the upper arm can be estimated as well. With these two estimates, the constraint of the elbow can be used for more accuracy. The joint constraint that is given by the elbow regards the sensor frames of each body segment.



The x axis of the upper arm sensor frame, the vector that is normal to the shoulder, is normal to a plane. No matter how the arm moves, the y axis of the forearm sensor frame is always in that plane. This means that the angle between the x axis of the upper frame and the y axis of the forearm frame, the adduction angle γ, is always 90 degrees.

By using the orientation estimates, an estimated adduction angle can be found. By subtracting the estimated adduction angle from 90 degrees, the adduction angle error of the orientation estimates can be calculated. Then, the sensor frames can each be rotate by 50% of the adduction angle error so that the new estimated adduction angle is 90 degrees. The axis in which the sensor frames are rotated is the cross product of the x axis from the upper frame and the y axis for the forearm frame. This method should provide a more accurate orientation estimate that fits the constraints of the human body.

Results

The sensor fusion of the gyroscope and accelerometer worked well, as the gyroscope picked up the change in orientation well and the accelerometer provided a good reference point for the gyroscope to compare to. The accelerometer's pitch angle estimation was slightly off, estimating 4 degrees when it should have been 0 degrees. The yaw angle estimation slowly became more inaccurate over time as the estimation was only based on the gyroscope.

Conclusions

Future investigations could include using more anatomical constraints and using a magnetometer which measures magnetic fields to help with the yaw angle estimation. This motion-capture system should be implemented with a camera motion capture system to see if it helps with accuracy.

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