A Novel Motion-Capture System:

Using the Kalman Filter to Fuse Inertial Sensor Data

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2017-2018

Abstract: This project used an accelerometer and a gyroscope to estimate the orientation of the arm in real time. The orientation of the arm was defined as the pitch, roll, and yaw rotation angles of the arm. (pitch represents the rotation around the y-axis, roll represents the rotation around the x-axis, and yaw represents the rotation around the z-axis) To estimate the orientation of the forearm and upper arm the Kalman Filter was used, which fused the sensors' data together. The joint constraint of the elbow was used to increase the accuracy of the estimation. In the end, the motion capture system was able accurately track the pitch and roll orientation angles, while the yaw angle estimate accuracy decreased 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 created an inertial motion-capture system using accelerometers, gyroscopes and the Kalman filter to estimate the orientation of the arm. In this project, an orientation estimate of the forearm was first made with the accelerometer. Then the gyroscope data was incorporated for a more accurate estimate. Finally, another accelerometer and gyroscope were used to find the orientation of the upper arm, and the joint constraint of the elbow made a more accurate estimation, allowing for arm motion tracking in real time.

Design Plan

This project used a Raspberry Pi and 2 MPU-6050s, one for the forearm and one for the upper arm, to estimate the orientation of the arm. The MPU-6050 had both an accelerometer and gyroscope and interfaced with the Raspberry Pi using the I2C protocol.

<u>Kalman Filter</u>

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 a more accurate estimation.

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

$$x_t = Ax_{t-1} + Bu_{t-1} + w_t$$

The filter models the measurement vector, which is a measurement of the state from a sensor, 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 priori estimate using the previous estimate and the control input. The error covariance matrix representing the uncertainty in the estimate, P, was also estimated.

$$x_t^- = Ax_{t-1} + Bu_{t-1}$$

$$P_t^- = AP_{t-1}A^T + Q$$

Q represents the process noise covariance matrix. 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, was calculated to update the state vector in a way that would minimize the error covariance matrix P. R represents the measurement noise covariance matrix.

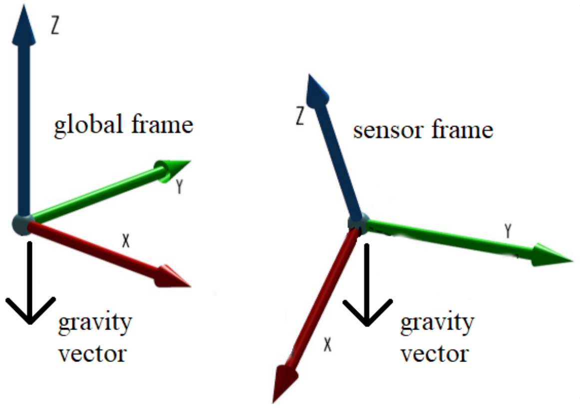
$$K_t = P_t^- H^T (HP_t^- H^T + R)^{-1}$$

$$x_t = x_t^- + K_t(z_t - Hx_t^-)$$

$$P_t = (I - K_t H)P_t^-$$

Accelerometer

Using just the accelerometer, the pitch and roll orientation angles of the forearm body segment could be estimated. To do this, the Kalman filter was 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 was estimated. The yaw orientation angle, the rotation around the z-axis, could not be determined from the accelerometer alone because as the body segment's yaw angle changes, the direction of gravity in the sensor frame does not.

The accelerometer signal vector, y, was a column vector with three elements that represents the accelerometer's x, y, and z measurements. It was 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 were estimated using the Kalman Filter. First, for the time update, a preliminary estimate was made by taking past estimates of the components and rotating them. The angular velocity of the body segment was approximated using the Small Angle approximation with the accelerometer signal vector.

$$\omega_t = \frac{n_{t-1} \times n_t}{T}$$

n represents the accelerometer signal vector and T represents the time between the two samples of the signal. The angular velocity approximation was used to rotate the previous component vector estimations to create the priori estimations. Then, the Kalman Filter's measurement update was used to find the final estimate of the accelerations, gravity, and offset. The estimate of the gravity vector was in terms of the sensor frame, so using trigonometry the pitch and roll angles were estimated.

$$roll = \arccos(\frac{g_z}{\sqrt{g_x^2 + g_y^2}})$$

$$pitch = \frac{g_x}{|g|}$$

Gyroscope

The gyroscope was used to provide complement the accelerometer orientation estimation by providing more accurate pitch and roll angle estimation while also creating a yaw angle estimation. Three separate Kalman Filter were used for the fusion of these sensors, one filter for each axis. In this instance of the filter, the state that was estimated was the orientation angles and the gyroscope offset.

$$x_t = \begin{bmatrix} \alpha_t \\ b_t \end{bmatrix}$$

α_t represents the estimated orientation angle and b_t represents the gyroscope offset. The gyroscope output was not the measurement vector, in this case the control input, u, was the gyroscope output. The measurement vector, z, in this case is the orientation estimate from the accelerometer.

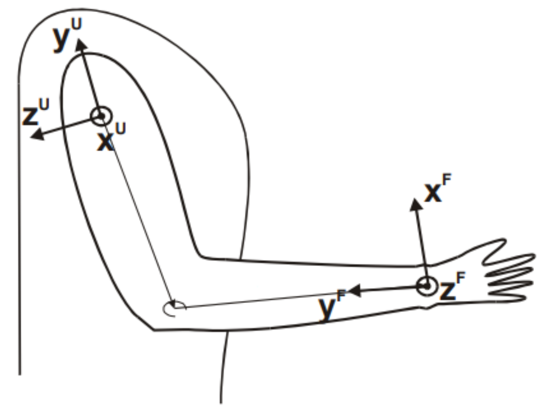
$$z = [\alpha_{t_{accel}}]$$

$$u = [\omega]$$

This made a preliminary estimate only using the gyroscope. Then, in the filter's measurement step, the accelerometer orientation estimate was used as a reference. This created a more accurate pitch and roll angle estimate. The yaw angle estimate was not as accurate because it relied only on the gyroscope.

Joint Constraint

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



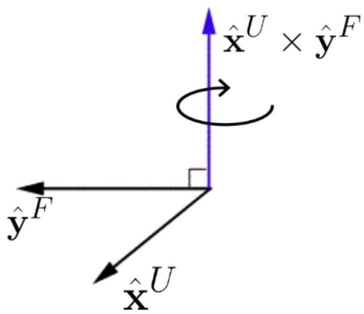
The x axis of the upper arm sensor frame, the vector that is normal to the shoulder, is normal to a 2D geometric plane. No matter how the arm moves, the y axis of the forearm sensor frame is always in that plane. This means that the x axis of the upper arm frame and the y axis of the forearm frame are orthogonal. The angle between them, the adduction angle γ, is always 90 degrees.

By using the orientation estimates, an estimated adduction angle could be found. By subtracting the estimated adduction angle from 90 degrees, the adduction angle error of the orientation estimates could be calculated.

$$\gamma^- = \arccos(x^U \times \mathrm{y}^\mathrm{F})$$

$$\gamma_\varepsilon = 90° - \gamma^-$$

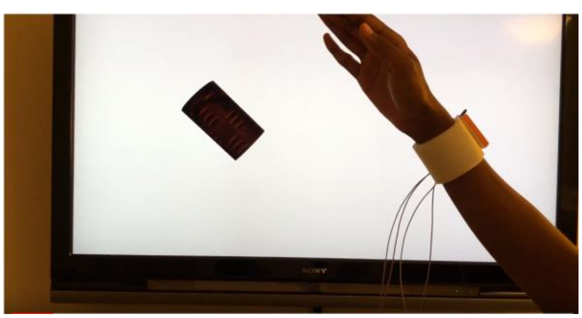
Then, the sensor frames were each rotated by 50% of the adduction angle error so that the new estimated adduction angle was 90 degrees. The axis in which the sensor frames are rotated is the cross product of the x axis from the upper frame and the y axis for the forearm frame.



This method provides 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. The joint constraint method was never tested, so its effect on the yaw angle accuracy is unknown.



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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