In lab4, the IMU had to be set up in order to gather position data for the robot. I also had to integrate the IMU data collection with the TOF sensor to send all important sensor data over bluetooth.

Set up the IMU

First, the IMU had to be hooked up to the artemis through the QWIIC connectors. Italian Trulli To set up the IMU in software, the ICM_20948 library had to be installed in the arduino ide in order to easily use the IMU with the artemis.

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AD0_VAL

One important variable in the example code is AD0_VAL. The AD0_VAL represents the last bit of the i2c address of the IMU. This value is only supposed to be 0 if the ADR jumper is closed, the value is 0. The ADR jumper is not closed, so the value is 0.

Acceleration and Gyroscope

When printing out the data from the demo, the accelerometer data shows the acceleration around each coordinate axis. The gyroscope measures the velocity around each coordinate axis. By calculating the angles between accelerations around each axis, the position of the object can be found. The position can also be found by using measured velocity around each axis to figure out the new position of the object, but this can lead to drift. Here is a video showing the output of manipulating the example code.

Your browser does not support the video tag. As can be seen from the video, when an axis is face perpendicular to the ground, the accel value goes to .001, but if it's parallel, then its value is 0. The gyroscope value increases around an axis as the IMU moves faster around a given axis.

Accelerometer

From class, we used the tangent between accelerations in each coordinate axis to figure out the angle the object is around the coordinate axis.

$$Roll_{accelerometer} = atan(a_x, a_z)$$

\

$$Pitch_{accelerometer} = atan(a_y, a_z)$$

\ , so using IMU.accX, IMU.accY, IMU.accZ as x y and z respectively, the pitch and roll could be calculated with

```
pitch_a = atan2(myICM.accY(), myICM.accZ()) * 180 / M_PI;
roll_a = atan2(myICM.accX(), myICM.accZ()) * 180 / M_PI;
```

yielding these results.

IMU at

$$0^\circ$$

roll and pitch Italian Trulli IMU at

$$+90^\circ$$

roll Italian Trulli IMU at

$$-90^\circ$$

roll Italian Trulli IMU at

$$+90^\circ$$

pitch Italian Trulli IMU at

$$-90^\circ$$

pitch Italian Trulli

Accelerometer accuracy

Here is a display of a 5s recording of 80 data points of the IMU pitch at each angle (-90,0,90 degrees). The arrays at the top are the means and standard deviations of each angle respectively. Italian Trulli As can be seen. The accelerometer provides great accuracy with the low pass filter (discussed later), but has a mean that is slightly off. 90 degrees is 83 degrees and 0 degrees yields -3 degrees. I chalked this difference up to my building not being level as my apartment is slightly crooked and the offset was consistent with the tilt of the house.

Here is the same analysis for roll. Italian Trulli Italian Trulli The accuracy is slightly better being generally 1 degree within the expected angle.

Noise in the frequency spectrum analysis

When collecting accelerometer data with no large noise source around, the data yielded this FFT, Italian Trulli When collecting data with the car motors being driven at max speed next to it, the data produced this FFT Italian Trulli As can be seen, there is after about 20Hz. This means the cutoff frequency should be around 15Hz

Therefore from class, \

$$\alpha = \frac{T}{T + RC}$$

\

$$f_c = \frac{1}{2\pi RC}$$

,so

$$RC = \frac{1}{2\pi f_c}$$

\

$$\alpha = \frac{T}{T + \frac{1}{2\pi f_c}}$$

, where

$$T = \frac{1}{\text{sample rate}}$$

, so since

$$T \simeq \frac{5s}{80} = 0.0625s$$

, \

$$\alpha = \frac{0.0625s}{0.0625s + \frac{1}{2\pi * 20Hz}} = 0.484$$

Unfortunately, with this low pass filter put in, the FFT doesn't yield much change. Italian Trulli

This is most likely due to the low magnitude of this noise since the IMU already has a low pass filter according to this figure from the datasheet. Italian Trulli I changed the alpha value to about .1 for a much lower frequency cut off.

In code, this low pass filter is implemented as discussed in class as

```
const float alpha = 0.1;
pitch_a_LPF[n] = alpha * pitch_a + (1 - alpha) * pitch_a_LPF[n - 1];
pitch_a_LPF[n - 1] = pitch_a_LPF[n];
roll_a_LPF[n] = alpha * roll_a + (1 - alpha) * roll_a_LPF[n - 1];
roll_a_LPF[n - 1] = roll_a_LPF[n];
```

Gyroscope

For the gyroscope, this uses the change in angle around each axis the glean the position of the object around each axis by using this equation from class, \

$$\theta_g = \theta_g - \text{gyr\_reading} * dt$$

\ so the angles were calculated like this

```
dt = (micros() - last_time) / 1000000.;
last_time = micros();
pitch_g = pitch_g + myICM.gyrX() * dt;
roll_g = roll_g - myICM.gyrY() * dt;
yaw_g = yaw_g + myICM.gyrZ() * dt;
```

If you compare the output of the gyroscope and filtered accelerometer data, you get these results. Italian Trulli Italian Trulli Italian Trulli As can be seen, the gyroscope data follows the same pattern as the accelerometer data, but is offset and this offset grows as time goes on.

When I decreased the sample rate, the gyroscope became much more choppy and updated to the new angles much more slowly, so keeping the gyroscope readings at the maximum possible sample rate was important for accuracy.

Complementary Filter

To make the complementary filter, the equation from class, \

$$\theta = (\theta + \theta_g * dt)(1 - \alpha) + \theta_a \alpha$$

\ was used in code, this was implemented as

```
roll_c = (roll_c + myICM.gyrY() * dt) * 0.9 + roll_a * 0.1;
pitch_c = (pitch_c + myICM.gyrX() * dt) * 0.9 + pitch_a * 0.1;
```

Here is another accuracy analysis like that done on the other sensors but for the complementary filter
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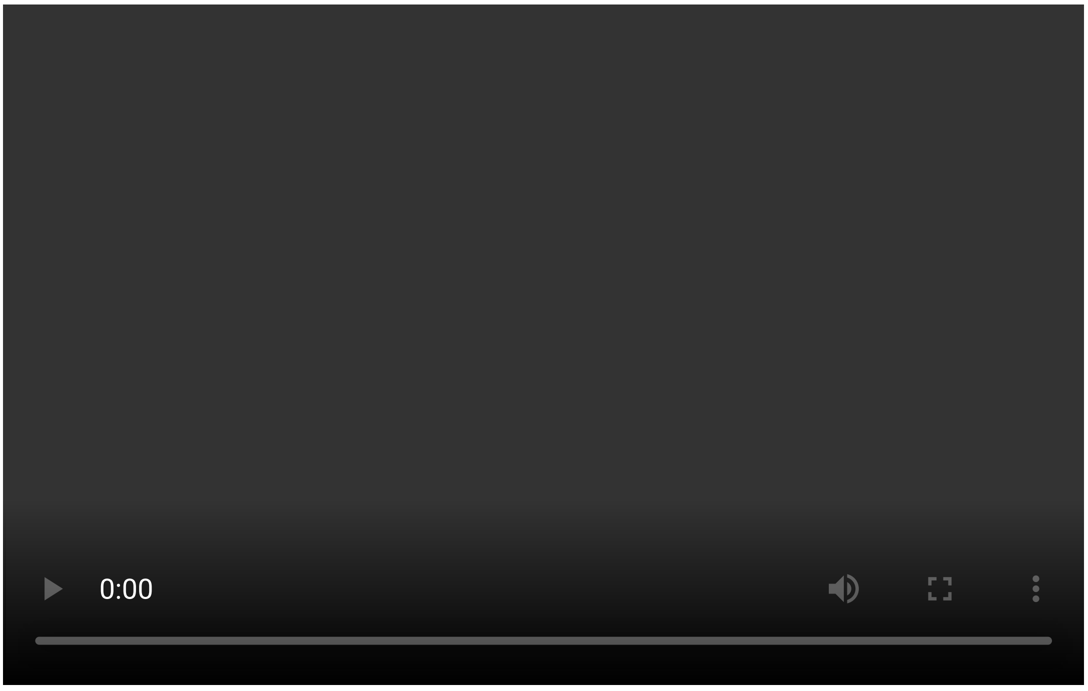
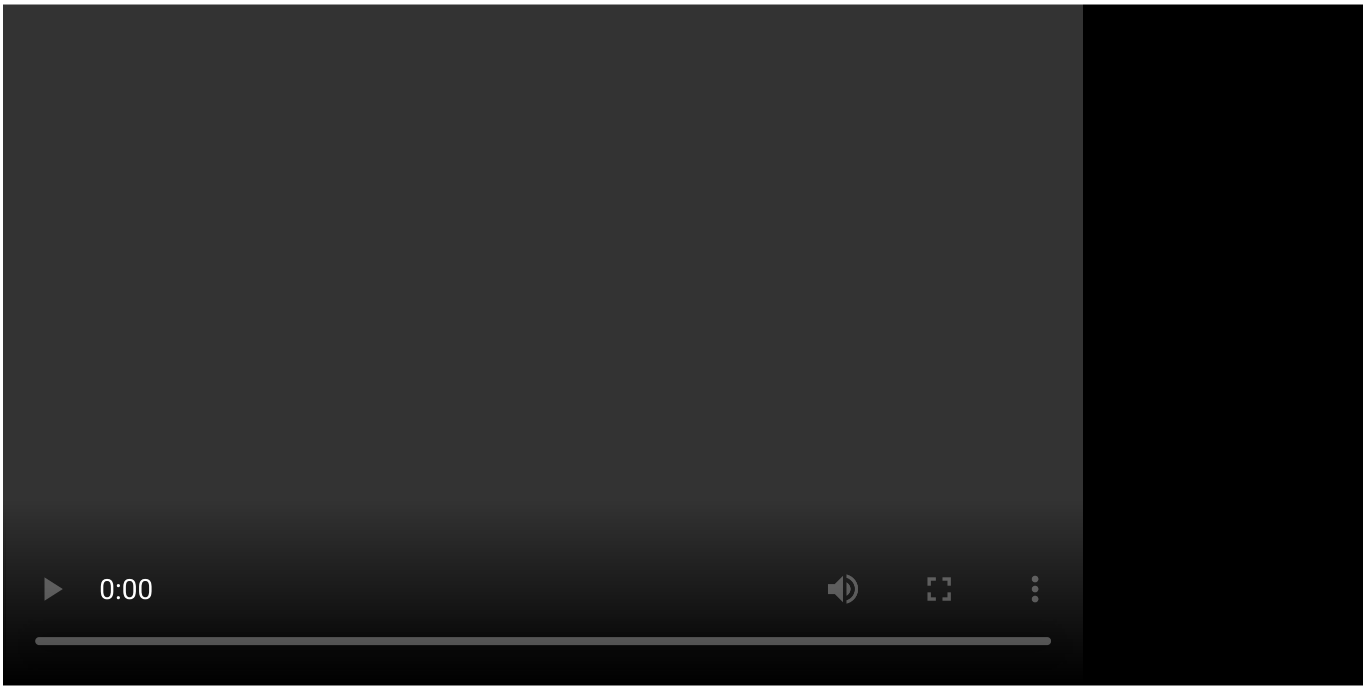
These videos also show the filter's resistance to small vibrations as well as showing its range



Your browser does not support the video tag. Here, you can see small vibrations in the IMU don't cause the measurement to move more than a few degrees.



This video shows how the filter has a range of 180 degree as it goes down to -180 after surpassing 180 degrees across both axis.

Speed of sampling

After speeding up the sensor data collection by removing print statements and making the collection interrupt based. Inside of a data collection loop, I can get a delay of about 0.04s between collections, so a 25Hz sampling rate. This is limited mostly by the fact that I collect sensor data once all sensors are available so one sensor could be the bottleneck. The data collection was pseudo-interrupt based by only collecting data after myICM.dataReady() was true.

Bluetooth integration

To integrate the IMU with the bluetooth code. The same procedure as explained in Lab3 was done, but this time using the data collection mechanism in the IMU_DEMO code, so a command GET_AGMT_5s_RAPID command was made. When this command is received, the calculations explained previously as well as the TOF data collection in lab3 is done. These are all sent in a string. like this,

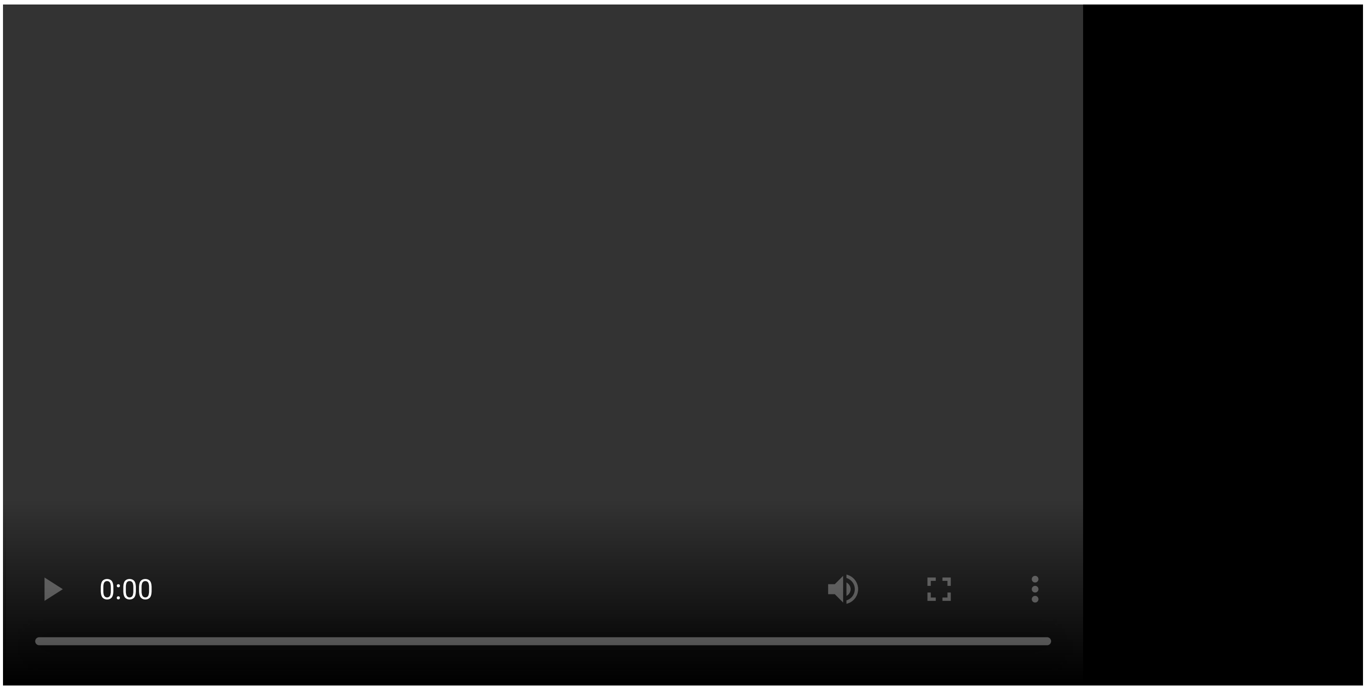
```
tx_estring_value.append("T:");
tx_estring_value.append(timeBuff[i]);
tx_estring_value.append("|");
tx_estring_value.append("P:");
tx_estring_value.append(pitchBuff[i]);
tx_estring_value.append("|");
tx_estring_value.append("R:");
tx_estring_value.append(rollBuff[i]);
tx_estring_value.append("|");
tx_estring_value.append("Y:");
tx_estring_value.append(yawBuff[i]);
tx_estring_value.append("|");
tx_estring_value.append("D1:");
tx_estring_value.append(dist1Buff[i]);
tx_estring_value.append("|");
```

```
tx_estring_value.append("D2:");
tx_estring_value.append(dist2Buff[i]);
```

Hear you can see the data is in buffers rather than just a value. This is because of the speed of sensor data collection. To produce the fastest sampling rate, collection was completed before sending the array, so a buffer was made for each value and the values were collected and then sent to the python code index by index. The data was stored in seperate arrays rather than one large array as if it's later decided to capture IMU data at a different time than TOF data, another time array can be added. Another issue is also the types of the values. Distance values are floats, but IMU values are int16_t, so an array with a constant type would be hard to manage. When I first allocated the arrays, I allocated 1000 values for each array, but with some values as floats and others as int16_t, these 4 byte values were too large and I ran into a stack overflow. 100 values for each array sufficed as the loop could only capture 80 values and this was only about 19200Kb, much less than the memory of the artemis as opposed to the 192000Kb if a 1000 length array were used. With the 384kB internal data, this is 3840s of data if all arrays were floats at a 25Hz sample rate, so the artemis has plenty of memory for data collection.

Here is an example of data collected over bluetooth. Italian Trulli

And here is an example video of the data collection



One problem I had was that after a data collection or two, the first few seconds of data would be slowly transitioning from the roll and pitch values from last data collection to the current roll and pitch value. To remedy this, after the command was received, the artemis code would read but not store data from the sensors for about 50 cycles which would allow the sensors to stabilize before data collection.

```
for (int i = 0; i < 50; i++)
  {
    while (!myICM.dataReady())
    {
    }
    myICM.getAGMT();
```

```
    setAGMT(&myICM); // This function takes into account the scale settings from when the measurement was made to calculate the values with units
}
```

Batteries

There are three batteries I was given, two 650mhAh batteries and a 850mhAh battery. The 650 battery is for the artemis as the artemis doesn't consume much power, but the 850mhAh battery is for the motor drivers that will later be inserted as the motor drivers require a larger amount of power.

Artemis Connected to battery

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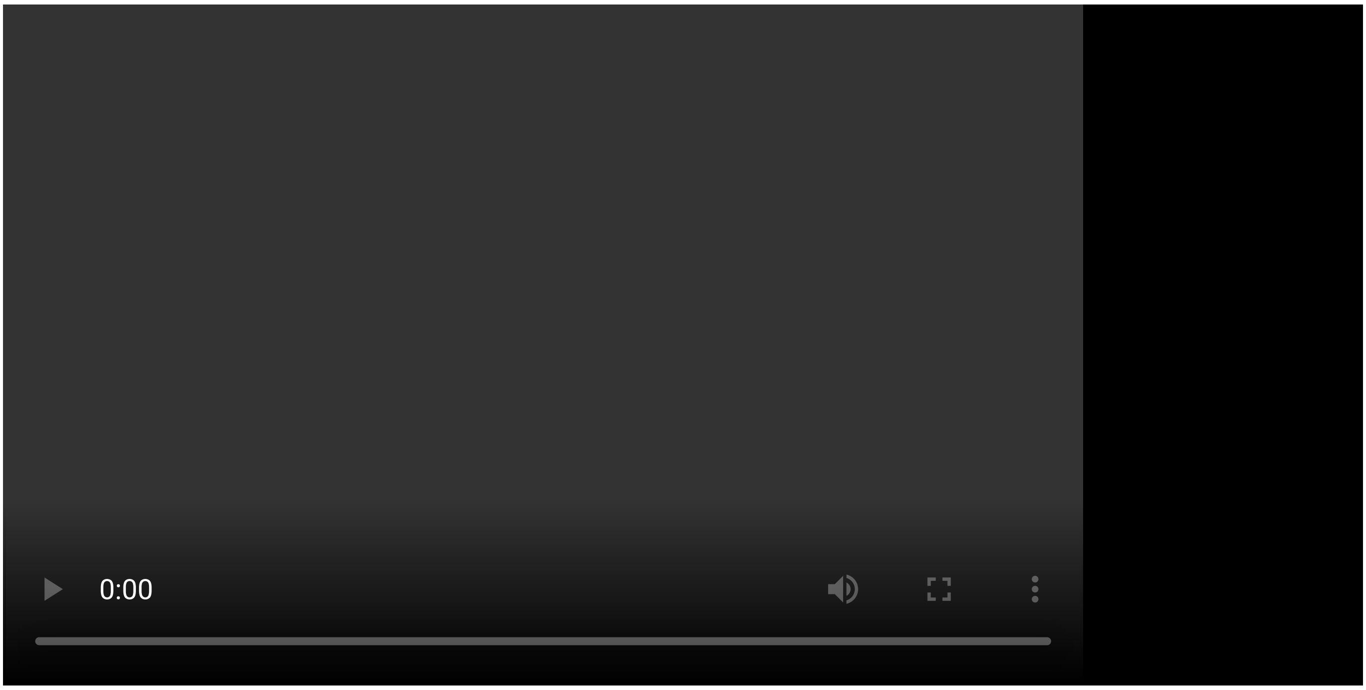
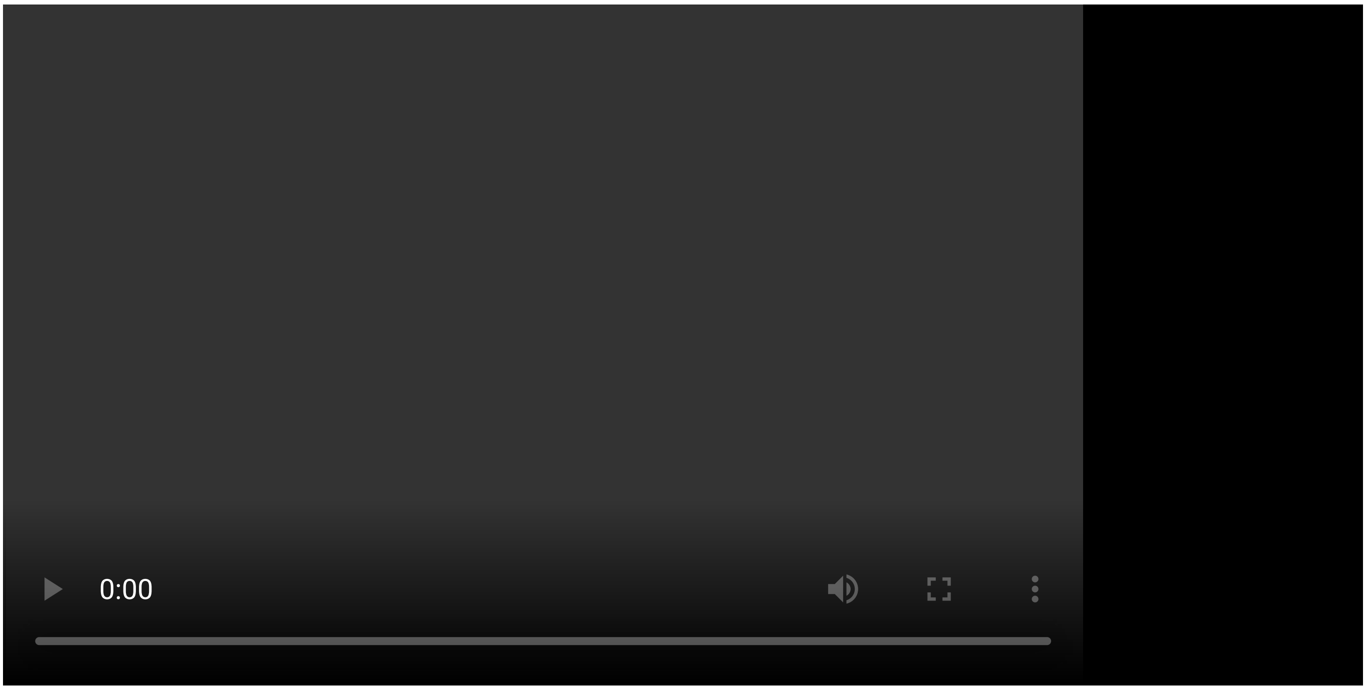
Record a Stunt



Stunt with artemis



You can see the data from the stunt in the video, but these graphs make it more clear. Italian Trulli As can be seen from this graph, the roll and pitch oscillate slightly as the slightly off horizontal imu rotates around the z axis. The yaw from the gyroscope though offset can be seen decreasing and increasing as the car rotates around its axis. Italian Trulli Unfortunately, one of the TOF sensors didn't show in the graph, but the other can be seen measuring about .1m which is facing towards the ground most likely as the side sensor points towards the ground. Near the end of the video, the TOF sensor falls onto the ground thus bringing the distance measurement close to 0.