acceleration_analysis

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1 Acceleration Analysis

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Relevant Links: - Slack Discussion: https://ubcsolar.slack.com/archives/C05CALTRK6V/p1759383966933329 - Monday Item: https://ubcsolar26.monday.com/boards/9565353662/pulses/18162773792

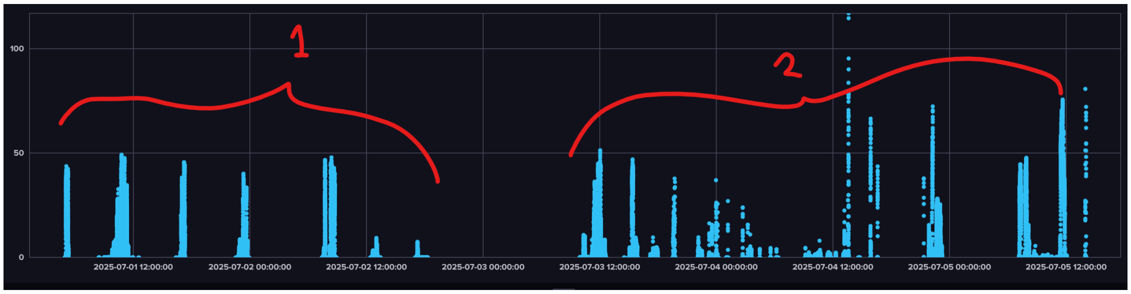
1.1 Imports

[1]:
```
import numpy as np
import matplotlib.pyplot as plt
from data_tools import query
from datetime import datetime
import pytz
```

1.2 Data Acquisition

First we have to determine the sections of time for which to analyze.

Here is a plot of MotorRotatingSpeed (km/h) for FSGP 2025 on InfluxDB. Section 1 is Scrutineering and section 2 is the track race. Note the 100km/h spike. I suspect this would be when were testing/debugging the motor.



InfluxDB *thinks* these are UTC timestamps. But I believe that our time zone conversions are still messed up, so I'll have to try to figure out for myself what the actual time was.

1.2.1 Scrutineering Timestamps

I'll start by getting some of the start/stop times for the "spikes" in section 1.

I get the times by hovering over the scatter plot and copying the first/last timestamps shown per section.

I have to tell Influx that it's UTC time, but the data has incorrect timestamps so this isn't actually the real time.

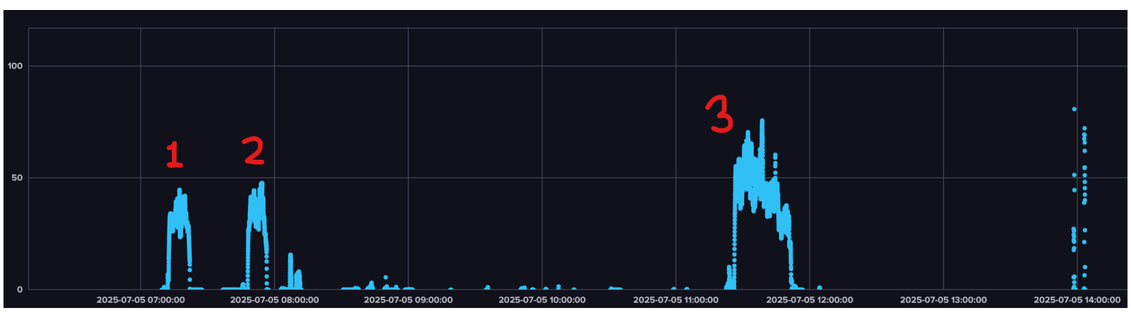
[2]:
```
# I hate this, but we have to convert local to UTC even though the local time␣
↪is wrong
hour_fix = 7

# start/stop time pairs
# These are the first thee 'spikes'
scrutineering_timestamps: list[tuple[datetime, datetime]] = [
    (datetime(2025, 7, 1, 4 + hour_fix, 58, 56, tzinfo=pytz.UTC),
     datetime(2025, 7, 1, 5 + hour_fix, 20, 10, tzinfo=pytz.UTC)),
    (datetime(2025, 7, 1, 8 + hour_fix, 29, 25, tzinfo=pytz.UTC),
     datetime(2025, 7, 1, 12 + hour_fix, 33, 53, tzinfo=pytz.UTC)),
    (datetime(2025, 7, 1, 16 + hour_fix, 24, 28, tzinfo=pytz.UTC),
     datetime(2025, 7, 1 + 1, (17 + hour_fix) - 24, 19, 22, tzinfo=pytz.UTC)),␣
↪# fix wraps to the next day
]
```

1.2.2 FSGP (Track Day) Timestamps

Looks like the best on-track data we have is around 1:30PM Central Time, July 5th (Timestamp courtesy of Deev). These laps were driven with UofT's motor, which could have slightly different acceleration characteristics.

The other two periods earlier that day are likely during motor testing.

This also confirms that **the timezone shown as UTC in InfluxDB is actually Vancouver time (UTC-7).**



[3]:
```
track_start_time = datetime(2025, 7, 5, 11 + hour_fix, 22, 41, tzinfo=pytz.UTC)
track_stop_time = datetime(2025, 7, 5, 11 + hour_fix, 56, 51, tzinfo=pytz.UTC)
```

1.2.3 Querying Data

[4]:
```
client = query.DBClient()

fields = ["MotorRotatingSpeed", "Acceleration_X", "Acceleration_Y",␣
 ↪"Acceleration_Z"]

print("Collecting Scrutineering Data")
raw_scrutineering_data = []
for i, section in enumerate(scrutineering_timestamps):
    section_data = {}
    print(f"    Querying Section {i + 1}")
    for field in fields:
        print(f"        Queried {field}!")
        section_data[field] = client.query_time_series(track_start_time,␣
 ↪track_stop_time, field)
    raw_scrutineering_data.append(section_data)

print("Collecting Track Day Data")
raw_track_data = {}
for field in fields:
    print(f"    Queried {field}!")
    raw_track_data[field] = client.query_time_series(track_start_time,␣
 ↪track_stop_time, field)
```

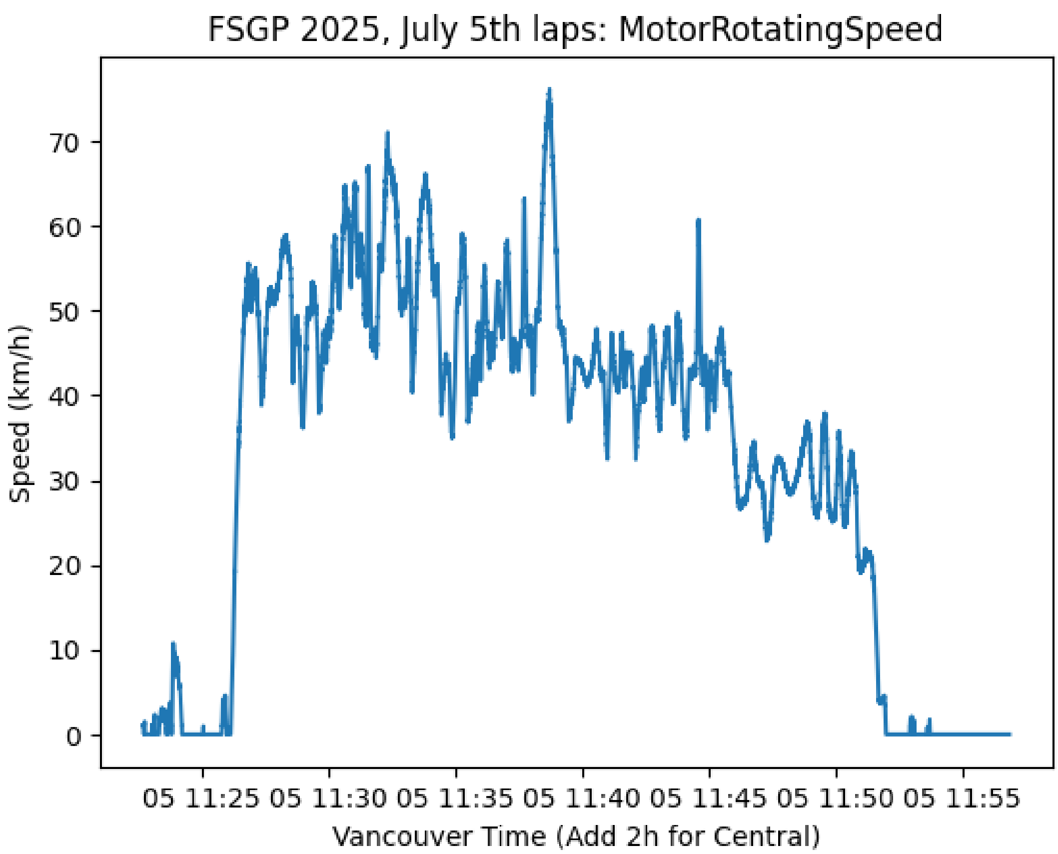
```
Collecting Scrutineering Data
    Querying Section 1
        Queried MotorRotatingSpeed!
        Queried Acceleration_X!
        Queried Acceleration_Y!
        Queried Acceleration_Z!
    Querying Section 2
        Queried MotorRotatingSpeed!
        Queried Acceleration_X!
        Queried Acceleration_Y!
        Queried Acceleration_Z!
    Querying Section 3
        Queried MotorRotatingSpeed!
        Queried Acceleration_X!
        Queried Acceleration_Y!
        Queried Acceleration_Z!
Collecting Track Day Data
    Queried MotorRotatingSpeed!
    Queried Acceleration_X!
    Queried Acceleration_Y!
    Queried Acceleration_Z!
```

1.3 Analysis

1.3.1 Sanity Check

Let's start with the on-track data, and verify that the speeds look right to start.

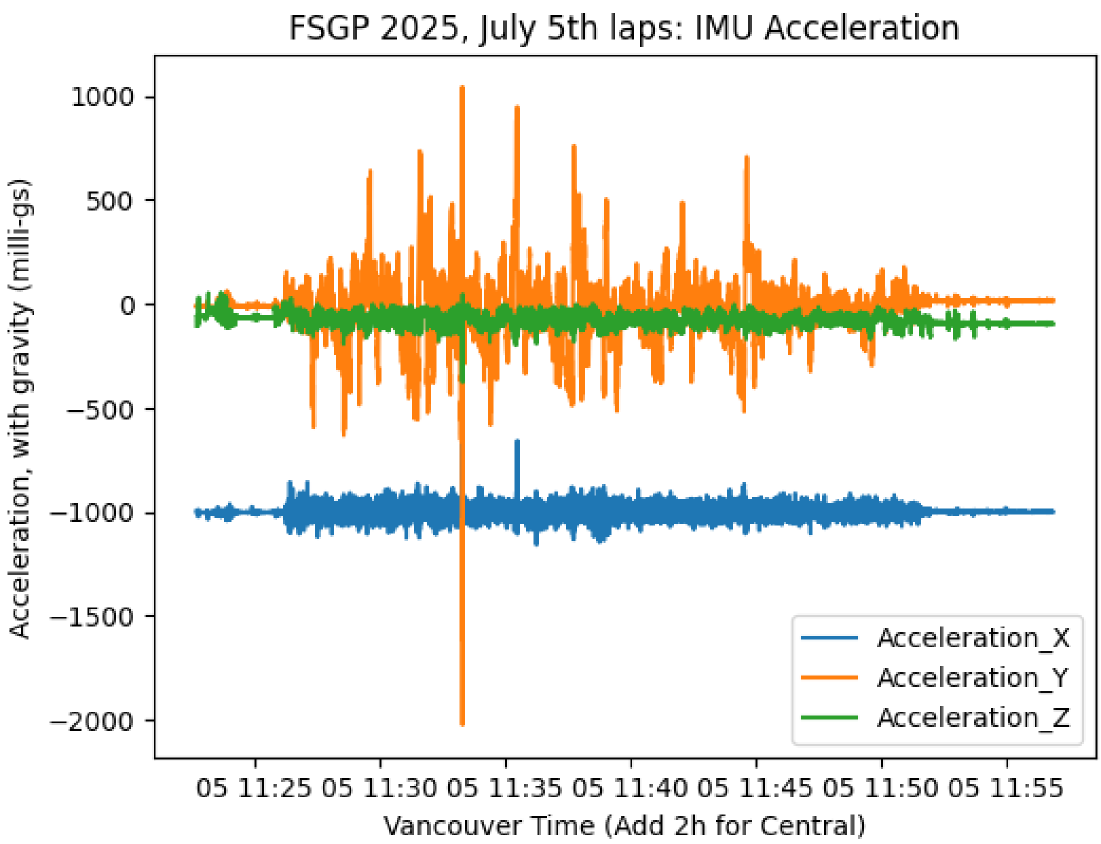
[5]:
```
plt.plot(raw_track_data["MotorRotatingSpeed"].datetime_x_axis,␣
↪raw_track_data["MotorRotatingSpeed"])
plt.ylabel("Speed (km/h)")
plt.xlabel("Vancouver Time (Add 2h for Central)")
plt.title("FSGP 2025, July 5th laps: MotorRotatingSpeed")
plt.show()
```



1.3.2 Time Domain Acceleration (raw)

[6]:
```
for direction in ("X", "Y", "Z"):
    plt.plot(raw_track_data[f"Acceleration_{direction}"].datetime_x_axis,␣
↪raw_track_data[f"Acceleration_{direction}"],
             label=f"Acceleration_{direction}")
plt.ylabel("Acceleration, with gravity (milli-gs)")
plt.xlabel("Vancouver Time (Add 2h for Central)")
```

```
plt.title("FSGP 2025, July 5th laps: IMU Acceleration")
plt.legend(loc="lower right")
plt.show()
```



1.3.3 Data Cleanup / Processing

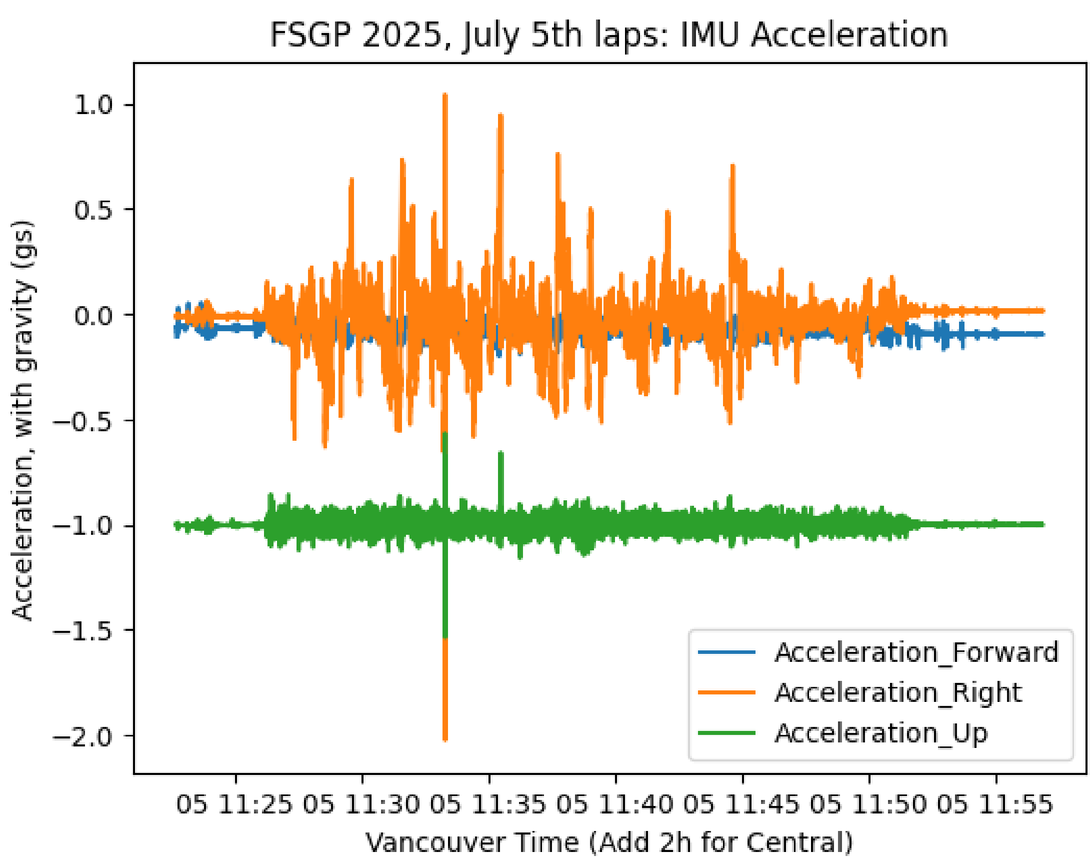
Converting Axes & Units A note on the IMU's X/Y/Z axes: - The X axis points up - The Y axis points to the right - The Z axis points forward

It's pretty awkward, so I'll convert the data. I'll also convert it to gs instead of milli-gs.

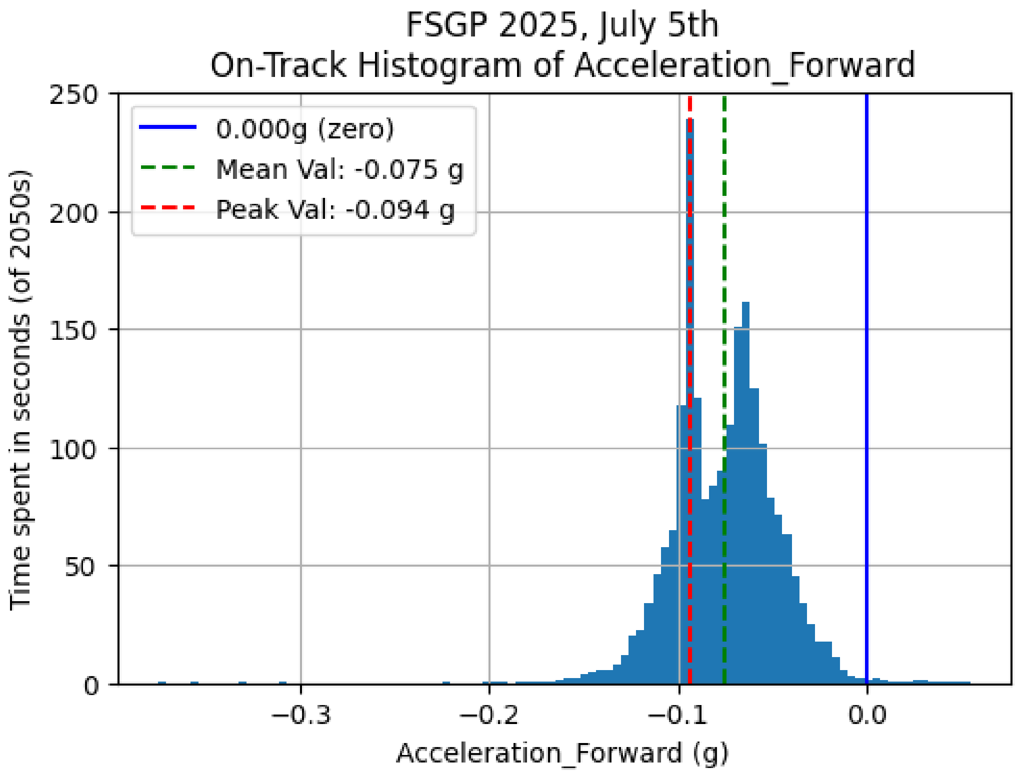
[7]:
```
def convert_accel_data(data: dict) -> dict:
    axis_map = {
        "Acceleration_X": "Acceleration_Up",
        "Acceleration_Y": "Acceleration_Right",
        "Acceleration_Z": "Acceleration_Forward",
    }
    processed_data = {}
    for key, val in data.items():
        if key in axis_map.keys():
            processed_data[axis_map[key]] = val / 1000. # convert to gs
```

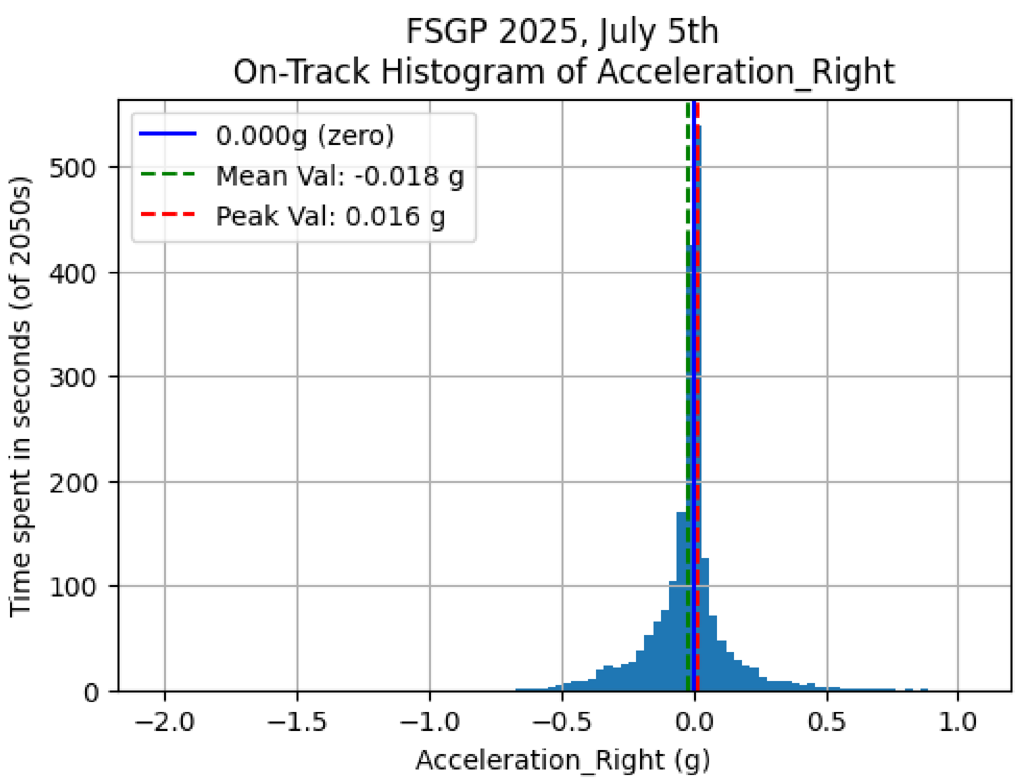
```
        else:
            processed_data[key] = val
    return processed_data

scrutineering_data = [convert_accel_data(raw_data) for raw_data in␣
 ↪raw_scrutineering_data]
track_data = convert_accel_data(raw_track_data)
```

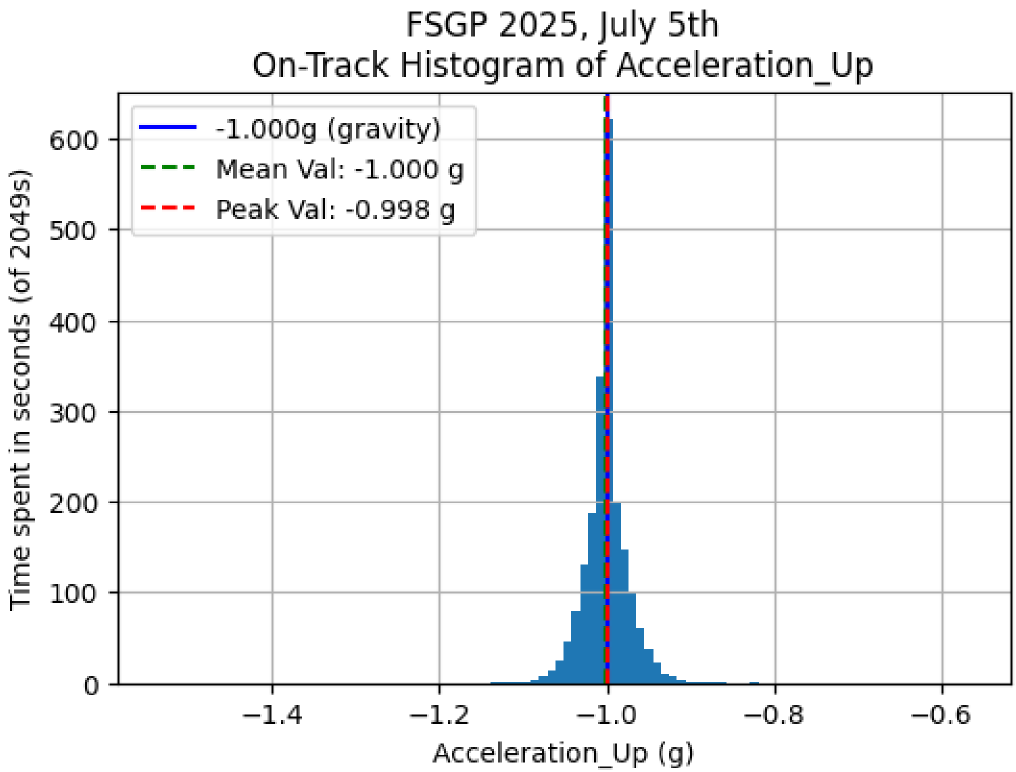
[8]:
```
for direction in ("Forward", "Right", "Up"):
    plt.plot(track_data[f"Acceleration_{direction}"].datetime_x_axis,␣
 ↪track_data[f"Acceleration_{direction}"],
             label=f"Acceleration_{direction}")
plt.ylabel("Acceleration, with gravity (gs)")
plt.xlabel("Vancouver Time (Add 2h for Central)")
plt.title("FSGP 2025, July 5th laps: IMU Acceleration")
plt.legend(loc="lower right")
plt.show()
```



```
[9]: mode_accelerations: dict[str, float] = {}
mean_accelerations: dict[str, float] = {}

for field in ("Acceleration_Forward", "Acceleration_Right", "Acceleration_Up"):
    hist, bins = np.histogram(track_data[field], bins=100)

    # The y-direction now corresponds to seconds with this norm
    time_hist = hist * track_data[field].period

    # Time in seconds
    on_track_time = track_data[field].length

    # Mean & (binned) mode
    mean_acceleration = track_data[field].mean()
    mean_accelerations[field] = mean_acceleration
    mode_acceleration = 0.5 * (bins[np.argmax(time_hist)] + bins[np.
↪argmax(time_hist) + 1])
    mode_accelerations[field] = mode_acceleration

    plt.figure(figsize=(6, 4))
    plt.stairs(time_hist, bins, fill=True)
    plt.ylabel(f"Time spent in seconds (of {on_track_time:.0f}s)")
    plt.xlabel(f"{field} (g)")
    plt.title(f"FSGP 2025, July 5th\nOn-Track Histogram of {field}")
    if field == "Acceleration_Up":
        plt.axvline(x=-1.0, color="b", label=f"-1.000g (gravity)")
        # plt.xlim(-2.0, 0.0)
    else:
        plt.axvline(x=0.0, color="b", label=f"0.000g (zero)")
        # plt.xlim(-1.0, 1.0)

    plt.axvline(x=mean_acceleration, color="g", linestyle="--", label=f"Mean␣
↪Val: {mean_acceleration:.3f} g")
    plt.axvline(x=mode_acceleration, color="r", linestyle="--", label=f"Peak␣
↪Val: {mode_acceleration:.3f} g")
    plt.legend(loc="upper left")
    plt.grid()
    plt.show()
```


FSGP 2025, July 5th
On-Track Histogram of Acceleration_Forward
0.000g (zero)
Mean Val: -0.075 g
Peak Val: -0.094 g
Time spent in seconds (of 2050s)
250
200
150
100
50
0
−0.3
−0.2
−0.1
0.0
Acceleration_Forward (g)


FSGP 2025, July 5th
On-Track Histogram of Acceleration_Right
0.000g (zero)
Mean Val: -0.018 g
Peak Val: 0.016 g
Time spent in seconds (of 2050s)
500
400
300
200
100
0
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
Acceleration_Right (g)



Fixing Bias We can see by the mean and peak values that some components have a slight bias. The upwards direction seems fine (within 0.002g of expected), the rightwards direction has some slight differences between the mean, the peak, and zero, and the forwards direction has a significant bias towards negative accelerations.

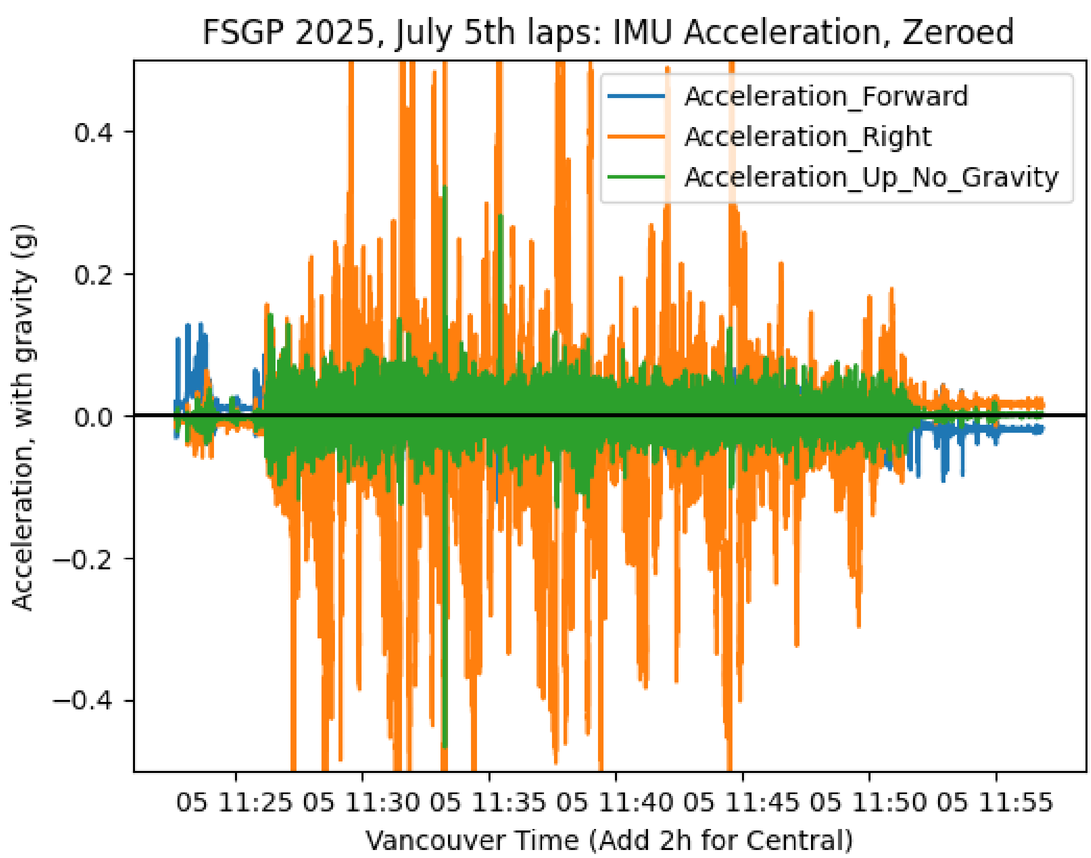
Based on the fact that a negative forward acceleration is still present when the car is stationary (see the time-domain plot), I believe that this is an error and should be removed.

Corrections performed: - Forward: subtract the mean, since we should expect the sum of acceleration to be 0 if we have no net change in velocity. - Up: add a version with 1 g added, to cancel out gravity - Right: This data seems fine; I'll leave it as-is

[10]:
```
# Align data so they have matching time domains
a_f_aligned, a_u_aligned, a_r_aligned = track_data["Acceleration_Forward"].
 ↪align(
    track_data["Acceleration_Forward"], track_data["Acceleration_Up"],␣
 ↪track_data["Acceleration_Right"]
)

track_data_zeroed = {
```

```
    "Acceleration_Forward": a_f_aligned -␣
↪mean_accelerations["Acceleration_Forward"],
    "Acceleration_Up": a_u_aligned,
    "Acceleration_Up_No_Gravity": a_u_aligned + 1.000,
    "Acceleration_Right": a_r_aligned
}
```

[11]:
```
for direction in ("Forward", "Right"):
    plt.plot(track_data_zeroed[f"Acceleration_{direction}"].datetime_x_axis,
             track_data_zeroed[f"Acceleration_{direction}"],
             label=f"Acceleration_{direction}")
plt.plot(track_data_zeroed["Acceleration_Up_No_Gravity"].datetime_x_axis,
             track_data_zeroed["Acceleration_Up_No_Gravity"],
             label=f"Acceleration_Up_No_Gravity")
plt.axhline(y=0.0, color='k')
plt.ylabel("Acceleration, with gravity (g)")
plt.xlabel("Vancouver Time (Add 2h for Central)")
plt.title("FSGP 2025, July 5th laps: IMU Acceleration, Zeroed")
plt.legend(loc="upper right")
plt.ylim(-0.5, 0.5)
plt.show()
```



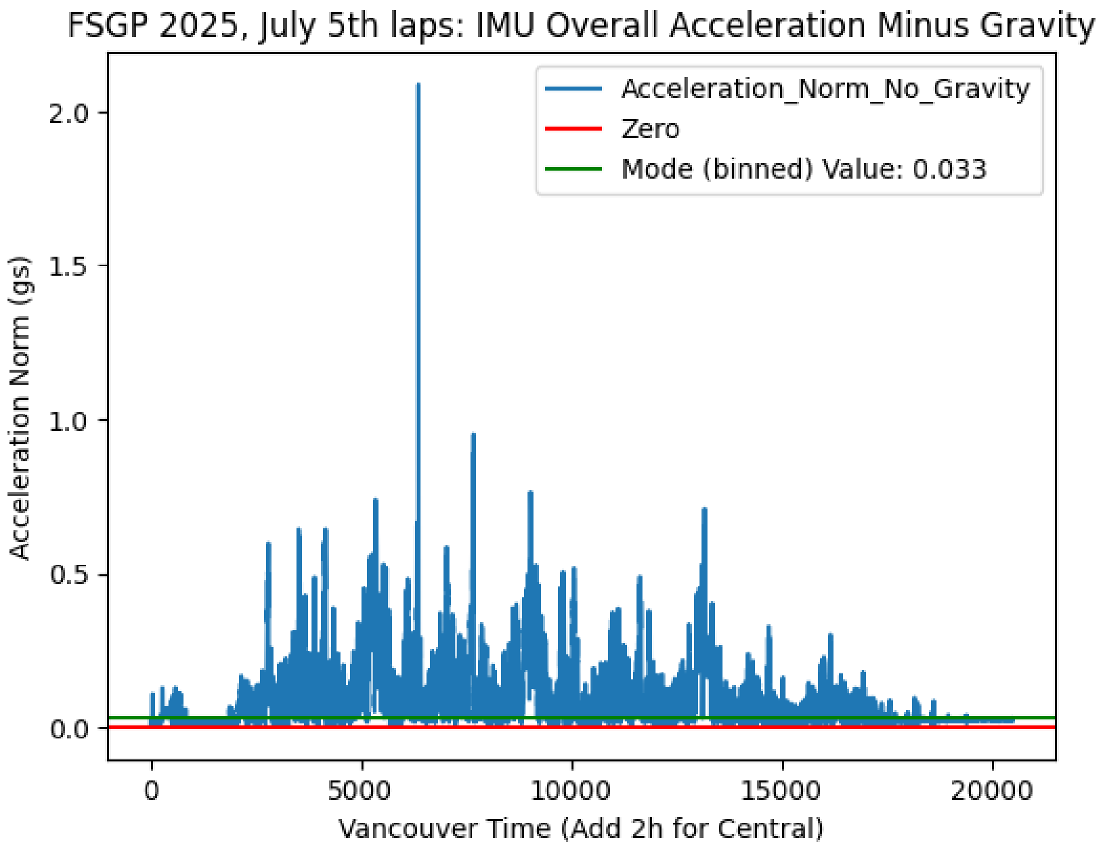
We can see from the above plot that the green (upwards) plot has almost no bias, but the orange and blue (right/forward) curves trend from positive to negative. I suspect this could occur when the car is not on level ground. Since the bias is pretty small relative to the actual values, I think it's appropriate to go forward with the analysis.

1.3.4 Computing The Norm

After the data has been adjusted for bias in `track_data_zeroed`, we can compute the acceleration norm.

[12]:
```
# Calculate the norm at any point in time using the pythagorean theorem

track_data_zeroed["Acceleration_Norm"] =␣
↪track_data_zeroed["Acceleration_Forward"].promote(np.linalg.norm([
    track_data_zeroed["Acceleration_Forward"],␣
↪track_data_zeroed["Acceleration_Right"], track_data_zeroed["Acceleration_Up"]
], axis=0))

track_data_zeroed["Acceleration_Norm_No_Gravity"] =␣
↪track_data_zeroed["Acceleration_Forward"].promote(np.linalg.norm([
    track_data_zeroed["Acceleration_Forward"],␣
↪track_data_zeroed["Acceleration_Right"],␣
↪track_data_zeroed["Acceleration_Up_No_Gravity"]
], axis=0))
```

[13]:
```
_h, _b = np.histogram(track_data_zeroed["Acceleration_Norm_No_Gravity"],␣
↪bins=100)
mode_value = 0.5 * (_b[np.argmax(_h)] + _b[np.argmax(_h) + 1])

plt.plot(track_data_zeroed["Acceleration_Norm_No_Gravity"],␣
↪label="Acceleration_Norm_No_Gravity")
plt.axhline(y=0.0, color="r", label="Zero")
plt.axhline(y=mode_value, color="g", label=f"Mode (binned) Value: {mode_value:.
↪3f}")
plt.ylabel("Acceleration Norm (gs)")
plt.xlabel("Vancouver Time (Add 2h for Central)")
plt.title("FSGP 2025, July 5th laps: IMU Overall Acceleration Minus Gravity")
plt.legend(loc="best")
plt.show()
```

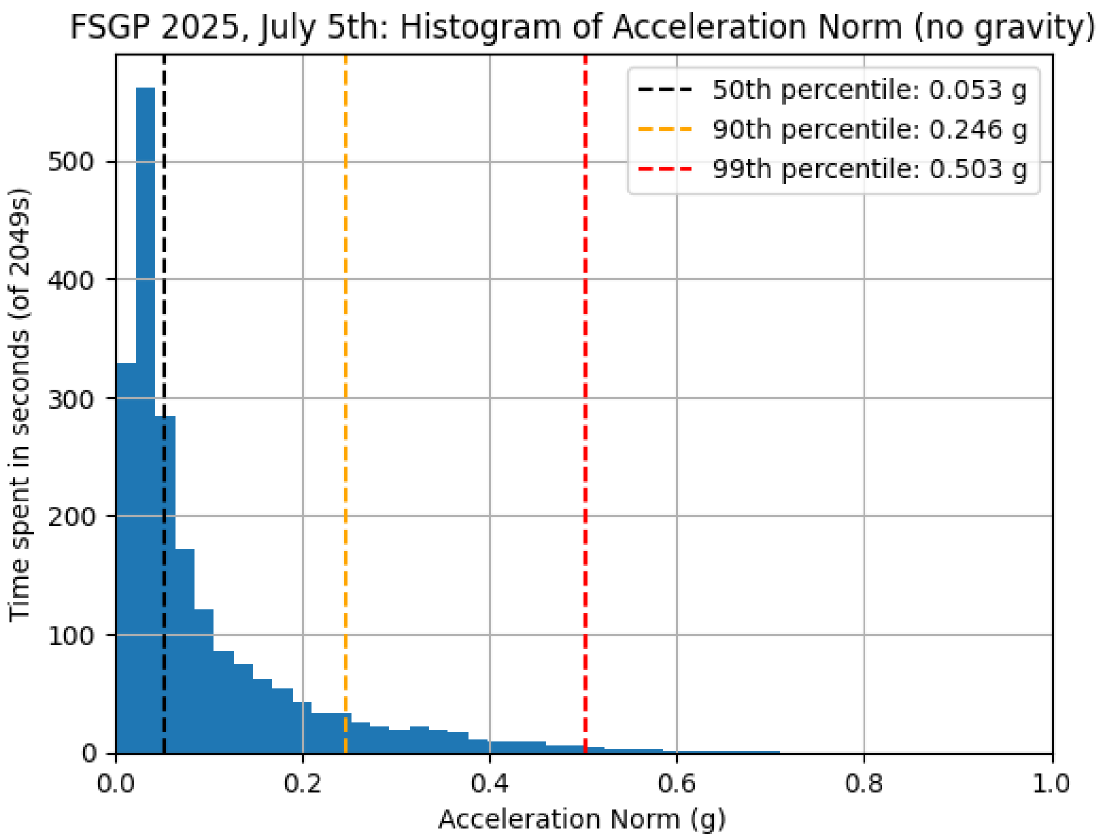


1.3.5 Norm Histograms

With bias removed and norm calculated, we can now plot the distribution of acceleration norms.

[14]:
```
# Each data
hist, bins = np.histogram(track_data_zeroed["Acceleration_Norm_No_Gravity"],␣
↪bins=100)

# The y-direction now corresponds to seconds with this norm
time_hist = hist * track_data_zeroed["Acceleration_Norm_No_Gravity"].period

# Time in seconds
on_track_time = track_data_zeroed["Acceleration_Norm_No_Gravity"].length

plt.stairs(time_hist, bins, fill=True)
plt.ylabel(f"Time spent in seconds (of {on_track_time:.0f}s)")
plt.xlabel("Acceleration Norm (g)")
plt.title("FSGP 2025, July 5th: Histogram of Acceleration Norm (no gravity)")
for percent_value, color in zip((50, 90, 99), ('black', 'orange', 'red')):
```

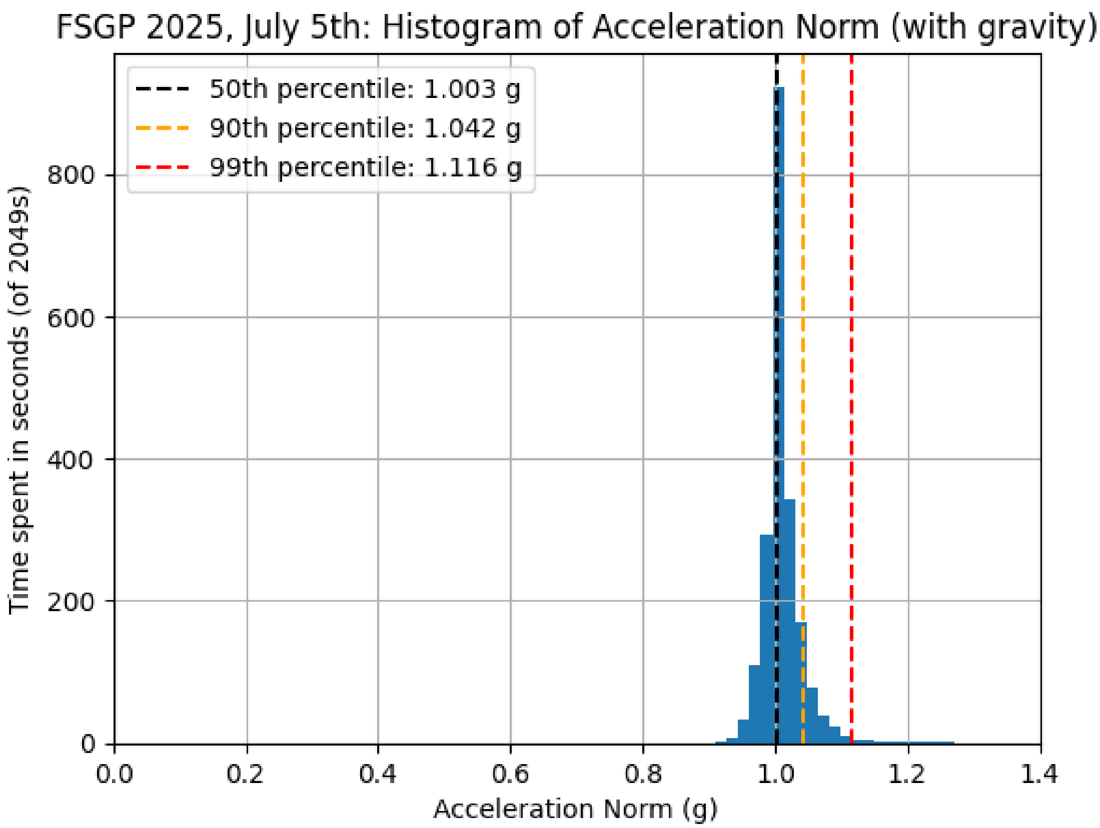
```
    percentile = np.
↪percentile(track_data_zeroed["Acceleration_Norm_No_Gravity"], percent_value)
    plt.axvline(x=percentile, linestyle="--", color=color,␣
↪label=f"{percent_value}th percentile: {percentile:.3f} g")
plt.legend(loc="best")
plt.xlim(0, 1.0)
plt.grid()
plt.show()
```



[15]:

```
# Each data
hist, bins = np.histogram(track_data_zeroed["Acceleration_Norm"], bins=100)

# The y-direction now corresponds to seconds with this norm
time_hist = hist * track_data_zeroed["Acceleration_Norm"].period

# Time in seconds
on_track_time = track_data_zeroed["Acceleration_Norm"].length

plt.stairs(time_hist, bins, fill=True)
plt.ylabel(f"Time spent in seconds (of {on_track_time:.0f}s)")
```

```
plt.xlabel("Acceleration Norm (g)")
plt.title("FSGP 2025, July 5th: Histogram of Acceleration Norm (with gravity)")
for percent_value, color in zip((50, 90, 99), ('black', 'orange', 'red')):
    percentile = np.percentile(track_data_zeroed["Acceleration_Norm"],␣
 ↪percent_value)
    plt.axvline(x=percentile, linestyle="--", color=color,␣
 ↪label=f"{percent_value}th percentile: {percentile:.3f} g")
plt.legend(loc="best")
plt.grid()
plt.xlim(0, 1.4)
plt.show()
```



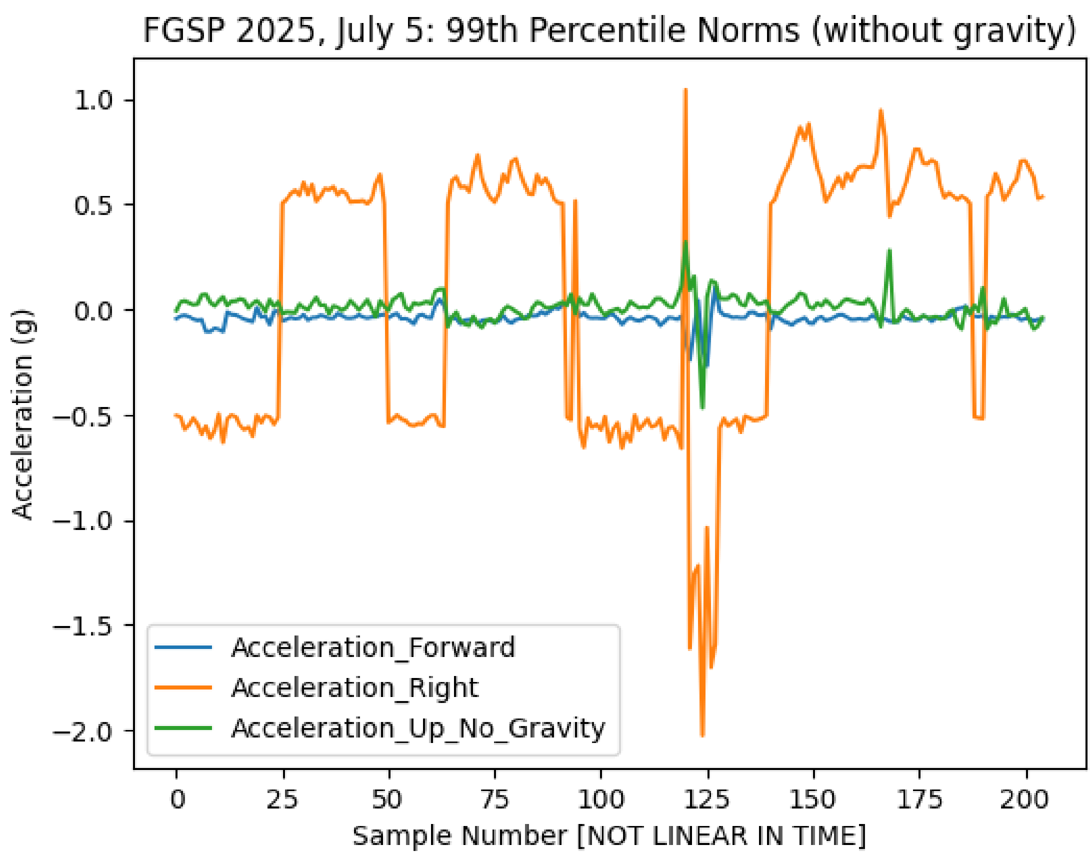
1.3.6 High-Loading Scenarios

Now we can take a closer look at the high-loading scenarios to see what their vector components look like.

Without Gravity

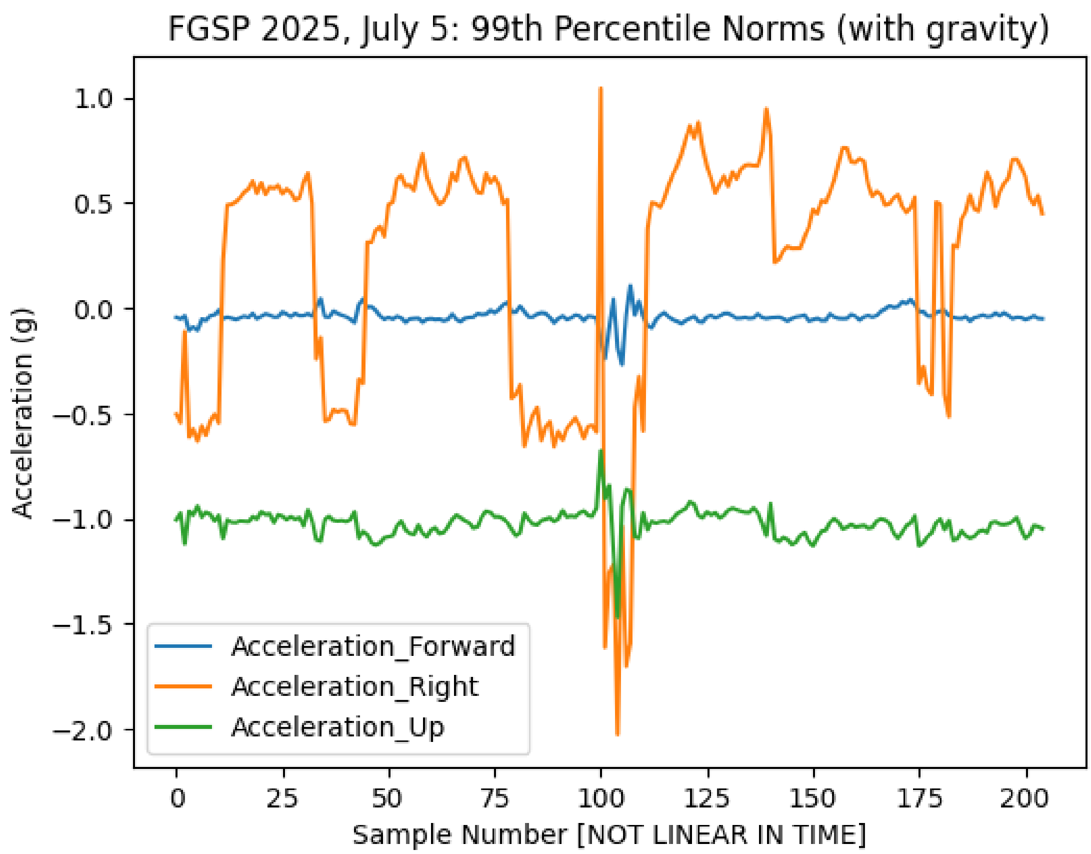
[16]:

```
p99 = np.percentile(track_data_zeroed["Acceleration_Norm_No_Gravity"], 99)
high_load_indices = np.where(track_data_zeroed["Acceleration_Norm_No_Gravity"]␣
↪> p99)

for direction in ("Forward", "Right", "Up_No_Gravity"):
    key = f"Acceleration_{direction}"
    plt.plot(track_data_zeroed[key][high_load_indices], label=key)
plt.legend(loc="best")
plt.title("FGSP 2025, July 5: 99th Percentile Norms (without gravity)")
plt.ylabel("Acceleration (g)")
plt.xlabel("Sample Number [NOT LINEAR IN TIME]")
plt.show()
```



[17]:
```
p99 = np.percentile(track_data_zeroed["Acceleration_Norm"], 99)
high_load_indices = np.where(track_data_zeroed["Acceleration_Norm"] > p99)

for direction in ("Forward", "Right", "Up"):
    key = f"Acceleration_{direction}"
    plt.plot(track_data_zeroed[key][high_load_indices], label=key)
```

```python
plt.legend(loc="best")
plt.title("FGSP 2025, July 5: 99th Percentile Norms (with gravity)")
plt.ylabel("Acceleration (g)")
plt.xlabel("Sample Number [NOT LINEAR IN TIME]")
plt.show()
```



Please note that the plots above do not really show a time axis. Rather, they should be thought of as a sequence of distinct points in time (on the x-axis), each with a certain vector acceleration that can be observed in the plot.

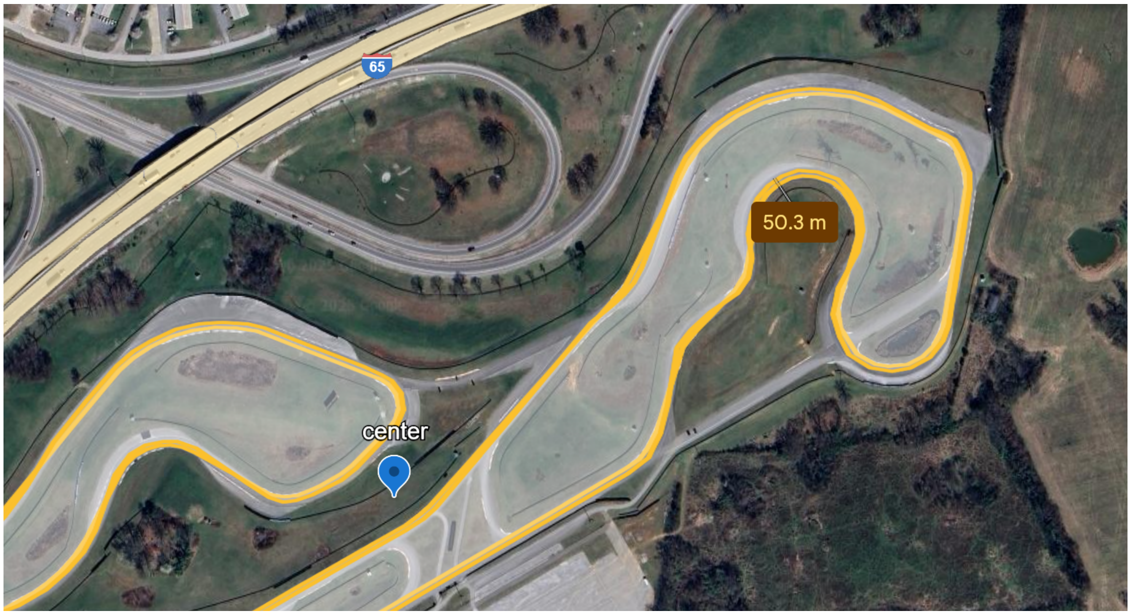
We observe that the instances where we have higher acceleration than normal are almost always happening when we have large left-right acceleration. This can be attributed to centripetal acceleration, which is given by

$$\frac{v^2}{\rho},$$

where v is the velocity and ρ is the radius of curvature.

Our peak acceleration is about 0.5 g in either side. We note from the first plot that our fast driving is around 15m/s (54km/h). And we can also measure the radius of curvature of the track using

Google Earth. I used the loop near the end of the track, even though it is not the tightest curve, because we know that drivers take this turns quickly as it is downhill.



So, if we compute the centripetal acceleration at $v = 15m/s$ and $\rho = 50m$, we get

$$a_c = \frac{v^2}{\rho} = \frac{(15m/s)^2}{50m} = \frac{225m^2/s^2}{50m} = 4.5m/s^2 \approx 0.46g$$

which roughly matches our data. This supports the hypothesis that most of our acceleration is centripetal acceleration due to driving around curves of the track.

[ ]: