h-inf-circle-after-trim

December 22, 2023

[41]:
```
import rosbag
import numpy as np
import matplotlib.pyplot as plt
from scipy.signal import butter, filtfilt
```

[42]:
```
bag = rosbag.Bag('/home/miguel/catkin_ws/src/crazyflie/crazyflie_controller/src/
 ↪data/h_inf_bag_after_circle_trim.bag')

position_optitrack = []
desired_position = []
vel_optitrack = []
desired_vel = []
control_input = []

for topic, msg, t in bag.read_messages(topics=['position_Optitrack',␣
 ↪'vel_Optitrack', 'desired_position', 'desired_vel', 'control_input']):

    if topic == 'position_Optitrack':
        position_optitrack.append((msg.x, msg.y, msg.z))

    if topic == 'vel_Optitrack':
        vel_optitrack.append((msg.x, msg.y, msg.z))

    if topic == 'desired_position':
        desired_position.append((msg.x, msg.y, msg.z))

    if topic == 'desired_vel':
        desired_vel.append((msg.x, msg.y, msg.z))

    if topic == 'control_input':
        control_input.append((msg.x, msg.y, msg.z))
bag.close()

position_optitrack = np.array(position_optitrack)
vel_optitrack = np.array(vel_optitrack)
desired_position = np.array(desired_position)
desired_vel = np.array(desired_vel)
```

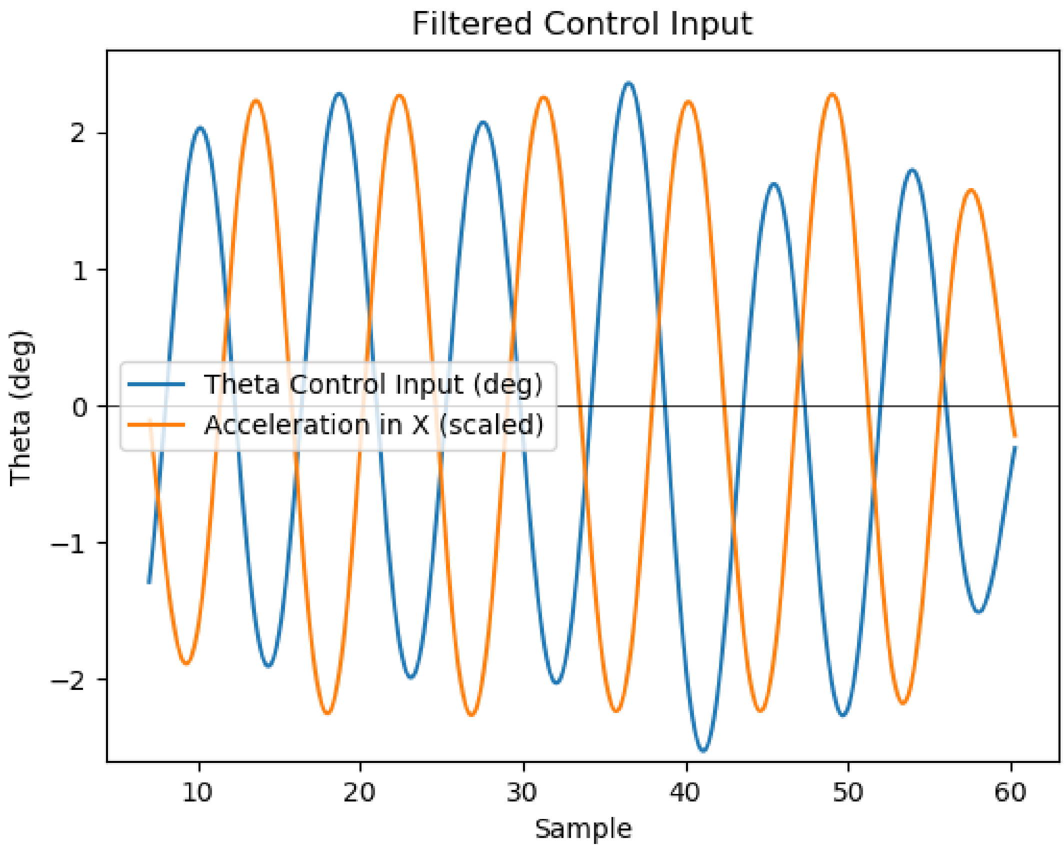
```
control_input = np.array(control_input)
```

[43]:
```
time = []
initial_time = 0
Ts = 1/30

for i in range(len(position_optitrack)):
    time.append(initial_time)
    initial_time+=Ts
```

1 X accel vs angle

[44]:
```
############### Finding the Acceleration ##################
# Filter parameters
N = 5  # Filter order
Wn = 0.01  # Cutoff frequency (as a fraction of the Nyquist frequency)
b, a = butter(N, Wn, 'low')

# Filter the velocity
vel_optitrack_ = np.array(vel_optitrack)[:, 0]
filtered_velocity = filtfilt(b, a, vel_optitrack_.squeeze())

# Numerical differentiation to find acceleration
dt = np.diff(time)  # Time intervals
acceleration = np.diff(filtered_velocity) / dt  # Numerical derivative


############## Filtering the Control Input ###############
control_input_ = np.array(control_input)[:, 0]
# Apply the filter
filtered_control_input = filtfilt(b, a, control_input_.squeeze())

# Convert to degrees
filtered_control_input_deg = np.rad2deg(filtered_control_input)

# Plotting
max_t = 18
min_t = 7
plt.plot(time[min_t*30:-max_t*30], filtered_control_input_deg[min_t*30:
↪-max_t*30], label='Theta Control Input (deg)')
plt.plot(time[(1+min_t*30):-max_t*30], [x*5 for x in acceleration[min_t*30:
↪-max_t*30]], label='Acceleration in X (scaled)')

plt.axhline(y=0, color='k', linewidth=0.5)
plt.ylim(-2.6, 2.6)
plt.xlabel('Sample')
```

```
plt.ylabel('Theta (deg)')
plt.title('Filtered Control Input')
plt.legend()
plt.show()
```



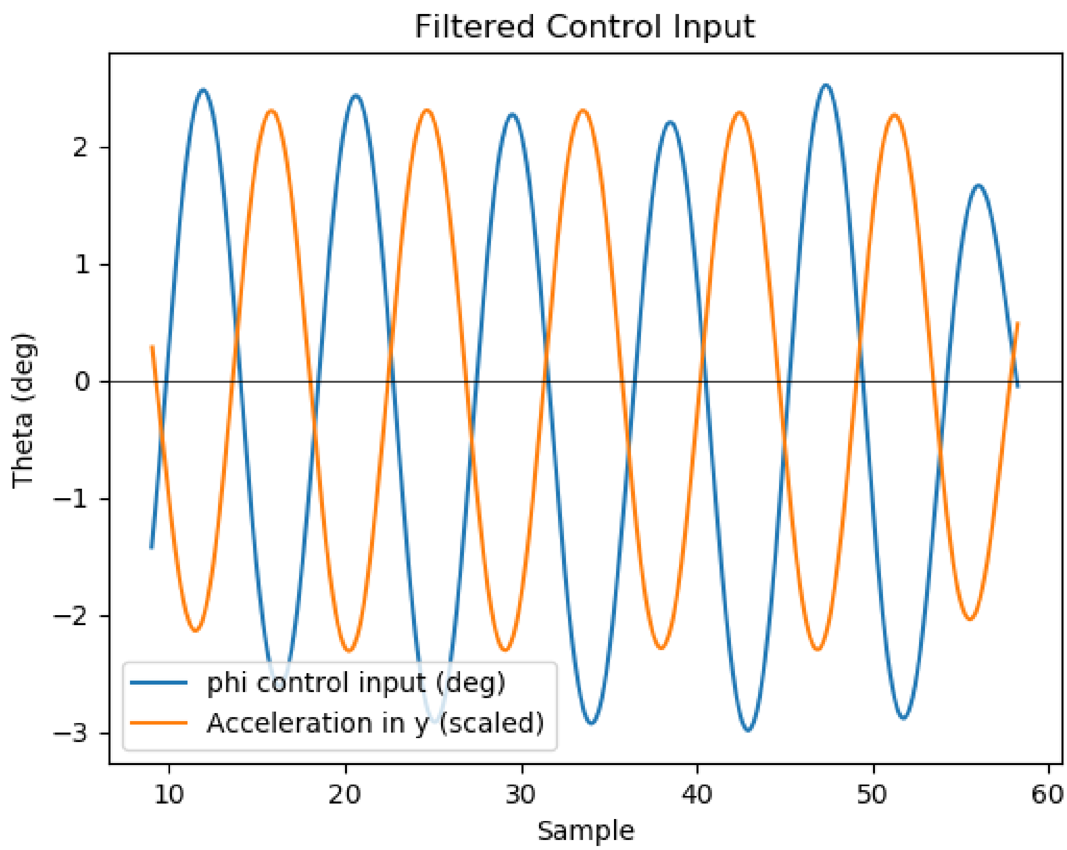
[45]:
```
np.mean(filtered_control_input_deg[min_t*30:-max_t*30])
```

[45]: -0.040919920039939696

2 Y accel vs angle

[46]:
```
############### Finding the Acceleration ##################
# Filter parameters
N = 5  # Filter order
Wn = 0.01  # Cutoff frequency (as a fraction of the Nyquist frequency)
b, a = butter(N, Wn, 'low')

# Filter the velocity
vel_optitrack_ = np.array(vel_optitrack)[:, 1]
```

```
filtered_velocity = filtfilt(b, a, vel_optitrack_.squeeze())

# Numerical differentiation to find acceleration
dt = np.diff(time)  # Time intervals
acceleration = np.diff(filtered_velocity) / dt  # Numerical derivative


############## Filtering the Control Input ###############
control_input_ = np.array(control_input)[:, 1]
# Apply the filter
filtered_control_input = filtfilt(b, a, control_input_.squeeze())

# Convert to degrees
filtered_control_input_deg = np.rad2deg(filtered_control_input)

# Plotting
max_t = 20
min_t = 9

plt.plot(time[min_t*30:-max_t*30], filtered_control_input_deg[min_t*30:
 ↪-max_t*30], label='phi control input (deg)')
plt.plot(time[(1+min_t*30):-max_t*30], [x*5 for x in acceleration[min_t*30:
 ↪-max_t*30]], label='Acceleration in y (scaled)')
plt.axhline(y=0, color='k', linewidth=0.5)
plt.xlabel('Sample')
plt.ylabel('Theta (deg)')
plt.title('Filtered Control Input')
plt.legend()
plt.show()
```

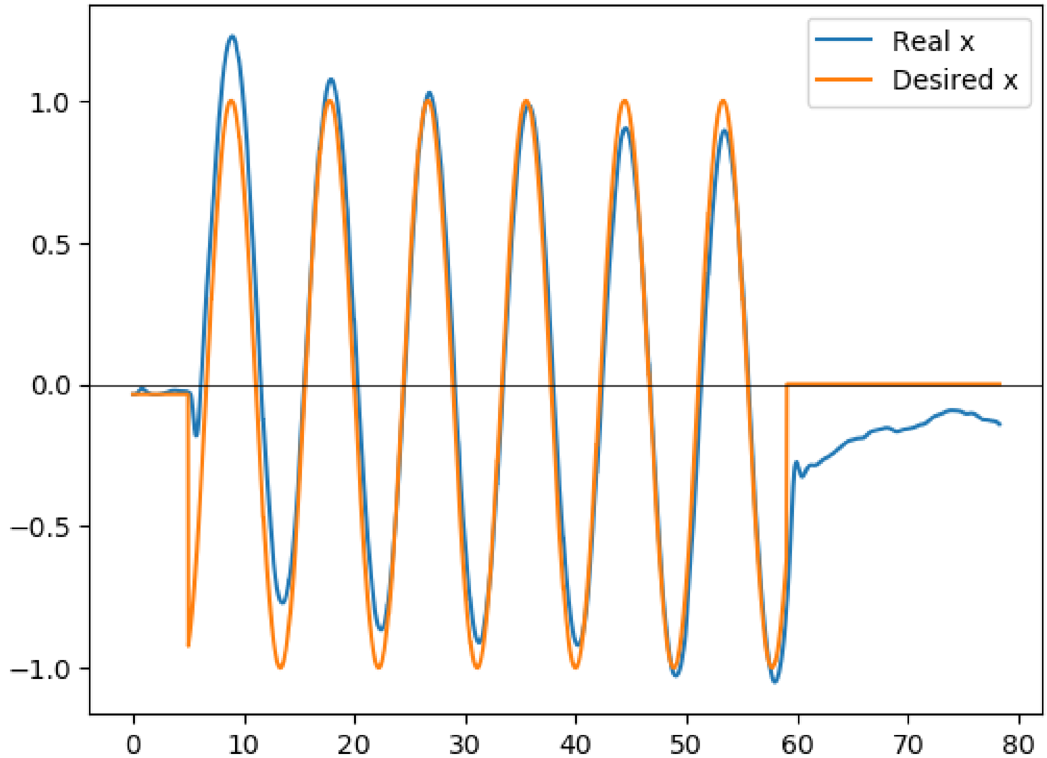


[47]:
```
np.mean(filtered_control_input_deg[10*30:-10*30])
```

[47]: -0.14622677548351967

3 X

[48]:
```
plt.plot(time, [x[0] for x in position_optitrack], label='Real x')
plt.plot(time, [x[0] for x in desired_position], label='Desired x')
plt.axhline(y=0, color='k', linewidth=0.5)
plt.legend()
plt.show()
```



3.0.1 X RMSE - Taking off the positioning task

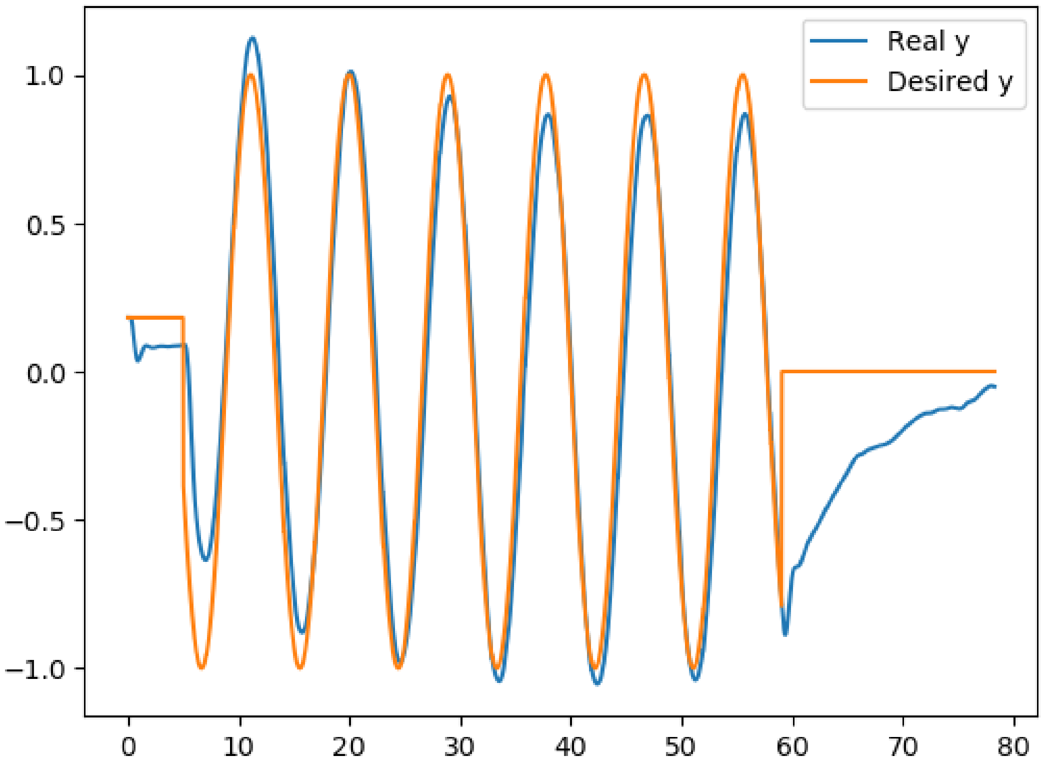
[49]:
```
x_square_error = (desired_position[6*30:-20*30, 1] - position_optitrack[6*30:
 ↪-20*30, 1])**2
x_mse = np.sqrt(np.mean(x_square_error))
x_mse
```

[49]: 0.15145306966952635

4 Y

[50]:
```
# Plotting example
plt.plot(time, [x[1] for x in position_optitrack], label='Real y')
plt.plot(time, [x[1] for x in desired_position], label='Desired y')

# Adding a horizontal line
#zplt.axhline(y=10, color='r', linewidth=0.5)
# plt.scatter(range(len(position_gaussian_error)), [x[2] for x in␣
 ↪position_gaussian_error], label='position_gaussian_error z', s=0.7)
# Add more plots as needed
# plt.ylim(0.92, 1.02)
```

```
plt.legend()
plt.show()
```



4.0.1 Y MSE - Taking off the positioning task

[51]:
```
y_square_error = (desired_position[10*30:-20*30, 1] - position_optitrack[10*30:
↪-20*30, 1])**2
y_mse = np.sqrt(np.mean(y_square_error))
y_mse
```

[51]: 0.139761953289191

5 Control Effort

5.1 Theta

[52]:
```
def control_effort(u):
    effort = 0
    for i in range(len(u) - 1):
        effort += u[i+1]-u[i]
```

```
    return effort

control_effort(np.array(control_input)[:, 0])
```

[52]: -0.031954224984525395

5.2 phi

[53]:
```
control_effort(np.array(control_input)[:, 1])
```

[53]: 0.02612478006957868

5.3 Thrust

[54]:
```
control_effort(np.array(control_input)[:, 2])
```

[54]: 0.03719884097512616

6 Conclusion

The accuracy of the drone has significantly improved just by adjusting the trim angles. Given the drone's small size, the markers have a substantial impact on its stability.

Regarding the error metrics, the H infinity control demonstrated excellent performance, exhibiting the smallest error among all the controllers during trajectory tracking. However, it should be noted that this controller takes a considerable amount of time to reach the desired position.

It's important to note that the H infinity controller was unable to effectively control the drone's z-axis positioning. Consequently, a Proportional-Derivative (PD) controller was implemented specifically to manage this aspect.