

```
In [1]: import Pkg
Pkg.activate(@__DIR__)
Pkg.instantiate()

import MathOptInterface as MOI
import Ipopt
import ForwardDiff as FD
import Convex as cvx
import ECOS
using LinearAlgebra
using Plots
using Random
using JLD2
using Test
import MeshCat as mc
using Printf
```

Activating project at `c:\CMU\SEM II\OCRL\16745---Optimal-Control-and-Reinforcement-Learning---Spring-2025\HW3_S25`

Q2: iLQR (30 pts)

In this problem, we are going to use iLQR to solve a trajectory optimization for a 6DOF quadrotor. This problem we will use a cost function to motivate the quadrotor to follow a specified aerobatic maneuver. The continuous time dynamics of the quadrotor are detailed in `quadrotor.jl`, with the state being the following:

$x = [r, v, {}^N_P{}^B, \omega]$ where $r \in \mathbb{R}^3$ is the position of the quadrotor in the world frame (N), $v \in \mathbb{R}^3$ is the velocity of the quadrotor in the world frame (N), ${}^N_P{}^B \in \mathbb{R}^3$ is the Modified Rodrigues Parameter (MRP) that is used to denote the attitude of the quadrotor, and $\omega \in \mathbb{R}^3$ is the angular velocity of the quadrotor expressed in the body frame (B). By denoting the attitude of the quadrotor with a MRP instead of a quaternion or rotation matrix, we have to be careful to avoid any scenarios where the MRP will approach its singularity at 360 degrees of rotation. For the maneuver planned in this problem, the MRP will be sufficient.

The dynamics of the quadrotor are discretized with `rk4`, resulting in the following discrete time dynamics function:

```
In [2]: include(joinpath(@__DIR__, "utils", "quadrotor.jl"))

function discrete_dynamics(params::NamedTuple, x::Vector, u, k)
    # discrete dynamics
    # x - state
    # u - control
    # k - index of trajectory
    # dt comes from params.model.dt
    return rk4(params.model, quadrotor_dynamics, x, u, params.model.dt)
end
```

`discrete_dynamics` (generic function with 1 method)

Part A: iLQR for a quadrotor (25 pts)

iLQR is used to solve optimal control problems of the following form:

$$\begin{aligned} \min_{x_{1:N}, u_{1:N-1}} \quad & \left[\sum_{i=1}^{N-1} \ell(x_i, u_i) \right] + \ell_N(x_N) \\ \text{st} \quad & x_1 = x_{IC} \\ & x_{k+1} = f(x_k, u_k) \quad \text{for } i = 1, 2, \dots, N-1 \end{aligned}$$

where x_{IC} is the initial condition, $x_{k+1} = f(x_k, u_k)$ is the discrete dynamics function, $\ell(x_i, u_i)$ is the stage cost, and $\ell_N(x_N)$ is the terminal cost. Since this optimization problem can be non-convex, there is no guarantee of convergence to a global optimum, or even convergence to a local optimum, but in practice we will see that it can work very well.

For this problem, we are going to use a simple cost function consisting of the following stage cost:

$$\ell(x_i, u_i) = \frac{1}{2}(x_i - x_{ref,i})^T Q (x_i - x_{ref,i}) + \frac{1}{2}(u_i - u_{ref,i})^T R (u_i - u_{ref,i})$$

And the following terminal cost:

$$\ell_N(x_N) = \frac{1}{2}(x_N - x_{ref,N})^T Q_f (x_N - x_{ref,N})$$

This is how we will encourage our quadrotor to track a reference trajectory x_{ref} . In the following sections, you will implement `iLQR` and use it inside of a `solve_quadrotor_trajectory` function. Below we have included some starter code, but you are free to use/not use any of the provided functions so long as you pass the tests.

We will consider iLQR to have converged when $\Delta J < \text{atol}$ as calculated during the backwards pass.

In [3]: # starter code: feel free to use or not use

```
function stage_cost(p::NamedTuple, x::Vector, u::Vector, k::Int)
    # TODO: return stage cost at time step k
    Q = p.Q
    R = p.R

    x_ref = p.Xref[k]
    u_ref = p.Uref[k]

    cost = 0.5*(x - x_ref)' * Q * (x - x_ref) + 0.5*(u - u_ref)' * R * (u - u_ref)
    return cost
end
function term_cost(p::NamedTuple, x)
    # TODO: return terminal cost
    Qf = p.Qf

    x_ref = p.Xref[end]

    cost = 0.5*(x - x_ref)' * Qf * (x - x_ref)
    return cost
end
function stage_cost_expansion(p::NamedTuple, x::Vector, u::Vector, k::Int)
    # TODO: return stage cost expansion
    # if the stage cost is J(x,u), you can return the following
    #  $\nabla_x^2 J$ ,  $\nabla_x J$ ,  $\nabla_u^2 J$ ,  $\nabla_u J$ 
     $\nabla_x^2 J$  = FD.hessian(x_ -> stage_cost(p, x_, u, k), x)
     $\nabla_x J$  = FD.gradient(x_ -> stage_cost(p, x_, u, k), x)
     $\nabla_u^2 J$  = FD.hessian(u_ -> stage_cost(p, x, u_, k), u)
     $\nabla_u J$  = FD.gradient(u_ -> stage_cost(p, x, u_, k), u)

    return  $\nabla_x^2 J$ ,  $\nabla_x J$ ,  $\nabla_u^2 J$ ,  $\nabla_u J$ 
end
function term_cost_expansion(p::NamedTuple, x::Vector)
    # TODO: return terminal cost expansion
    # if the terminal cost is  $J_n(x,u)$ , you can return the following
    #  $\nabla_x^2 J_n$ ,  $\nabla_x J_n$ 

     $\nabla_x^2 J$  = FD.hessian(x_ -> term_cost(p, x_), x)
     $\nabla_x J$  = FD.gradient(x_ -> term_cost(p, x_), x)

    return  $\nabla_x^2 J$ ,  $\nabla_x J$ 
end
function backward_pass(params::NamedTuple,          # useful params
                       X::Vector{Vector{Float64}}, # state trajectory
                       U::Vector{Vector{Float64}}) # control trajectory
    # compute the iLQR backwards pass given a dynamically feasible trajectory X and U
    # return d, K,  $\Delta J$ 

    # outputs:
    #   d - Vector{Vector} feedforward control
    #   K - Vector{Matrix} feedback gains
    #    $\Delta J$  - Float64 expected decrease in cost

    nx, nu, N = params.nx, params.nu, params.N

    # vectors of vectors/matrices for recursion
    P = [zeros(nx,nx) for i = 1:N] # cost to go quadratic term
    p = [zeros(nx)    for i = 1:N] # cost to go linear term
    d = [zeros(nu)    for i = 1:N-1] # feedforward control
    K = [zeros(nu,nx) for i = 1:N-1] # feedback gain

    # TODO: implement backwards pass and return d, K,  $\Delta J$ 
    N = params.N
     $\Delta J$  = 0.0

    P[N], p[N] = term_cost_expansion(params, X[N])
    Q = params.Q
    R = params.R
    Qf = params.Qf

    for k = N-1:-1:1
        # TODO: compute the feedback and feedforward terms
        A = FD.jacobian(x -> discrete_dynamics(params, x, U[k], k), X[k])
        B = FD.jacobian(u -> discrete_dynamics(params, X[k], u, k), U[k])

         $\nabla_x^2 J$ ,  $\nabla_x J$ ,  $\nabla_u^2 J$ ,  $\nabla_u J$  = stage_cost_expansion(params, X[k], U[k], k)
        gx =  $\nabla_x J$  + A'*p[k+1]
        gu =  $\nabla_u J$  + B'*p[k+1]

        Gxx =  $\nabla_x^2 J$  + A'*P[k+1]*A
    end
end
```

```

    Guu =  $\nabla_u^2 J$  + B'*P[k+1]*B
    Gxu = A'*P[k+1]*B
    Gux = B'*P[k+1]*A

    # Compute feedback and feedforward terms
    d[k] = Guu\gu
    K[k] .= Guu\Gux

    # Update cost-to-go
    p[k] = gx - K[k]*gu + K[k]*Guu*d[k] - Gxu*d[k]
    P[k] .= Gxx + K[k]*Guu*K[k] - Gxu*K[k] - K[k]*Gux

    # Expected cost reduction
    ΔJ += gu*d[k]
end

return d, K, ΔJ
end

function trajectory_cost(params::NamedTuple,           # useful params
                        X::Vector{Vector{Float64}},   # state trajectory
                        U::Vector{Vector{Float64}})    # control trajectory
    # compute the trajectory cost for trajectory X and U (assuming they are dynamically feasible)
    N = params.N

    cost = 0.0
    # TODO: add trajectory cost
    for k = 1:N-1
        cost += stage_cost(params, X[k], U[k], k)
    end
    cost += term_cost(params, X[N])

    return cost
end

function forward_pass(params::NamedTuple,             # useful params
                     X::Vector{Vector{Float64}},     # state trajectory
                     U::Vector{Vector{Float64}},     # control trajectory
                     d::Vector{Vector{Float64}},     # feedforward controls
                     K::Vector{Matrix{Float64}};     # feedback gains
                     max_linesearch_iters = 20)      # max iters on linesearch
    # forward pass in iLQR with linesearch
    # use a line search where the trajectory cost simply has to decrease (no Armijo)

    # outputs:
    #   Xn::Vector{Vector} updated state trajectory
    #   Un::Vector{Vector} updated control trajectory
    #   J::Float64         updated cost
    #   α::Float64         step length

    nx, nu, N = params.nx, params.nu, params.N

    Xn = [zeros(nx) for i = 1:N]      # new state history
    Un = [zeros(nu) for i = 1:N-1]    # new control history

    # initial condition
    Xn[1] = 1*X[1]

    # initial step length
    α = 1.0

    # TODO: add forward pass
    for i = 1:max_linesearch_iters

        # Try current step size α
        for k = 1:N-1
            # Apply feedback + feedforward control
            δx = Xn[k] - X[k]
            Un[k] = U[k] - α*d[k] - K[k]*δx

            # Roll out dynamics
            Xn[k+1] = discrete_dynamics(params, Xn[k], Un[k], k)
        end

        # Compute new trajectory cost
        Jn = trajectory_cost(params, Xn, Un)
        J = trajectory_cost(params, X, U)

        # If cost decreased, accept the step
        if Jn < J
            return Xn, Un, Jn, α
        end
    end
end

```

```

        # Otherwise reduce step size and reset trajectories
         $\alpha$  *= 0.5
        Xn[1] = X[1] # Reset initial state

    end

    error("forward pass failed")
end

```

forward_pass (generic function with 1 method)

```

In [4]: function ilQR(params::NamedTuple,      # useful params for costs/dynamics/indexing
                x0::Vector,                  # initial condition
                U::Vector{Vector{Float64}};  # initial controls
                atol=1e-3,                   # convergence criteria:  $\Delta J < atol$ 
                max_iters = 250,             # max ilQR iterations
                verbose = true)              # print logging

    # ilQR solver given an initial condition x0, initial controls U, and a
    # dynamics function described by `discrete_dynamics`

    # return (X, U, K) where
    # outputs:
    #   X::Vector{Vector} - state trajectory
    #   U::Vector{Vector} - control trajectory
    #   K::Vector{Matrix} - feedback gains K

    # first check the sizes of everything
    @assert length(U) == params.N-1
    @assert length(U[1]) == params.nu
    @assert length(x0) == params.nx

    nx, nu, N = params.nx, params.nu, params.N

    # TODO: initial rollout
    # Initial rollout from x0 using initial controls U
    X = [zeros(nx) for k = 1:N]
    X[1] = x0

    # Forward simulate using initial control sequence
    for k = 1:N-1
        X[k+1] = discrete_dynamics(params, X[k], U[k], k)
    end

    for ilqr_iter = 1:max_iters
        # backward pass
        d, K,  $\Delta J$  = backward_pass(params, X, U)
        # forward pass with line search
        X, U, J,  $\alpha$  = forward_pass(params, X, U, d, K)

        # termination criteria
        if  $\Delta J < atol$ 
            if verbose
                @info "ilQR converged"
            end
            return X, U, K
        end

        # -----logging -----
        if verbose
            dmax = maximum(norm.(d))
            if rem(ilqr_iter-1,10)==0
                @printf "iter      J           $\Delta J$       |d|           $\alpha$       \n"
                @printf "-----\n"
            end
            @printf("%3d    %10.3e %9.2e %9.2e %6.4f    \n",
                    ilqr_iter, J,  $\Delta J$ , dmax,  $\alpha$ )
        end
    end

    error("ilQR failed")
end

```

ilQR (generic function with 1 method)

```

In [5]: function create_reference(N, dt)
    # create reference trajectory for quadrotor
    R = 6
    Xref = [ [R*cos(t); R*cos(t)*sin(t); 1.2 + sin(t); zeros(9)] for t = range(-pi/2, 3*pi/2, length = N)]
    for i = 1:(N-1)
        Xref[i][4:6] = (Xref[i+1][1:3] - Xref[i][1:3])/dt
    end
    Xref[N][4:6] = Xref[N-1][4:6]
    Uref = [(9.81*0.5/4)*ones(4) for i = 1:(N-1)]
end

```

```

    return Xref, Uref
end
function solve_quadrotor_trajectory(;verbose = true)

    # problem size
    nx = 12
    nu = 4
    dt = 0.05
    tf = 5
    t_vec = 0:dt:tf
    N = length(t_vec)

    # create reference trajectory
    Xref, Uref = create_reference(N, dt)

    # tracking cost function
    Q = 1*diagm([1*ones(3);.1*ones(3);1*ones(3);.1*ones(3)])
    R = .1*diagm(ones(nu))
    Qf = 10*Q

    # dynamics parameters (these are estimated)
    model = (mass=0.5,
             J=Diagonal([0.0023, 0.0023, 0.004]),
             gravity=[0,0,-9.81],
             L=0.1750,
             kf=1.0,
             km=0.0245,dt = dt)

    # the params needed by iLQR
    params = (
        N = N,
        nx = nx,
        nu = nu,
        Xref = Xref,
        Uref = Uref,
        Q = Q,
        R = R,
        Qf = Qf,
        model = model
    )

    # initial condition
    x0 = 1*Xref[1]

    # initial guess controls
    U = [(uref + .0001*randn(nu)) for uref in Uref]

    # solve with iLQR
    X, U, K = iLQR(params,x0,U;atol=1e-4,max_iters = 250,verbose = verbose)

    return X, U, K, t_vec, params
end

```

solve_quadrotor_trajectory (generic function with 1 method)

In [6]: @testset "ilqr" begin

```

    # NOTE: set verbose to true here when you submit
    Xilqr, Uilqr, Kilqr, t_vec, params = solve_quadrotor_trajectory(verbose = true)

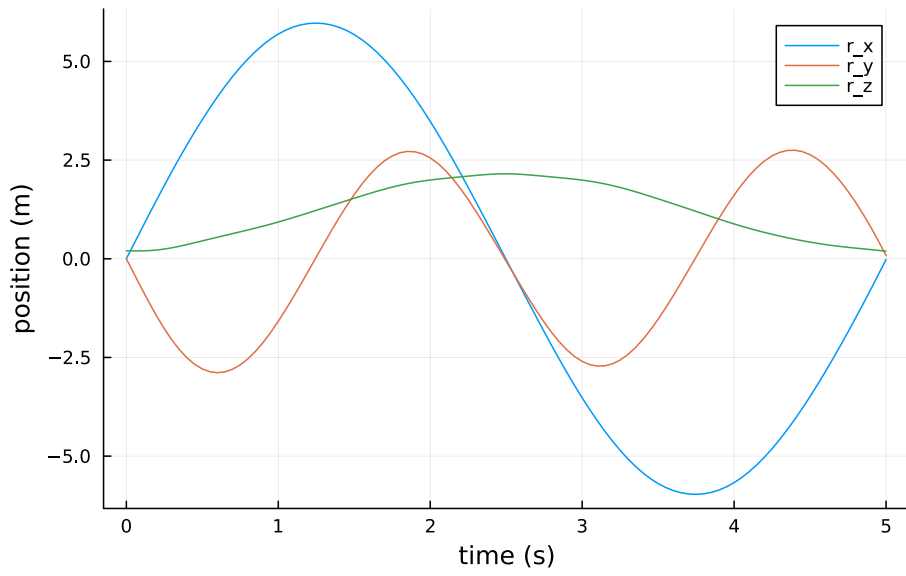
    # -----testing-----
    Usol = load(joinpath(@__DIR__,"utils","ilqr_U.jld2"))["Usol"]
    @test maximum(norm.(Usol .- Uilqr,Inf)) <= 1e-2

    # -----plotting-----
    Xm = hcat(Xilqr...)
    Um = hcat(Uilqr...)
    display(plot(t_vec, Xm[1:3,:]', xlabel = "time (s)", ylabel = "position (m)",
                 title = "Position", label = ["r_x" "r_y" "r_z"]))
    display(plot(t_vec, Xm[4:6,:]', xlabel = "time (s)", ylabel = "velocity (m/s)",
                 title = "Velocity", label = ["v_x" "v_y" "v_z"]))
    display(plot(t_vec, Xm[7:9,:]', xlabel = "time (s)", ylabel = "MRP",
                 title = "Attitude (MRP)", label = ["p_x" "p_y" "p_z"]))
    display(plot(t_vec, Xm[10:12,:]', xlabel = "time (s)", ylabel = "angular velocity (rad/s)",
                 title = "Angular Velocity", label = ["ω_x" "ω_y" "ω_z"]))
    display(plot(t_vec[1:end-1], Um', xlabel = "time (s)", ylabel = "rotor speeds (rad/s)",
                 title = "Controls", label = ["u_1" "u_2" "u_3" "u_4"]))
    display(animate_quadrotor(Xilqr, params.Xref, params.model.dt))
end

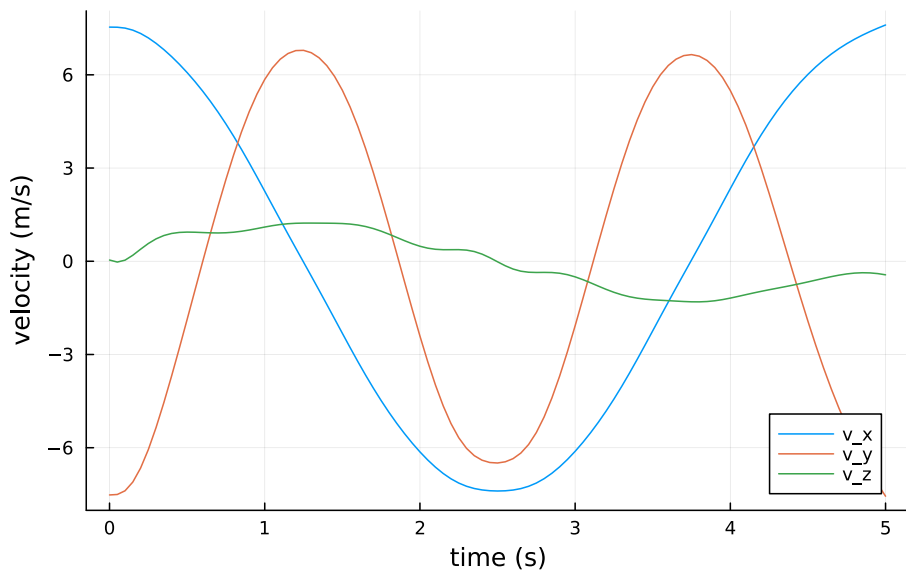
```

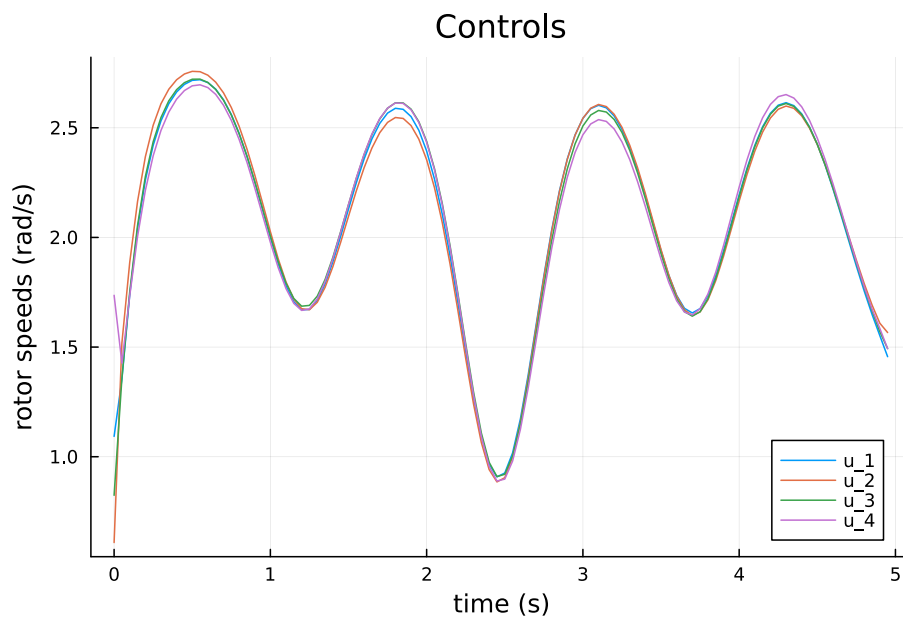
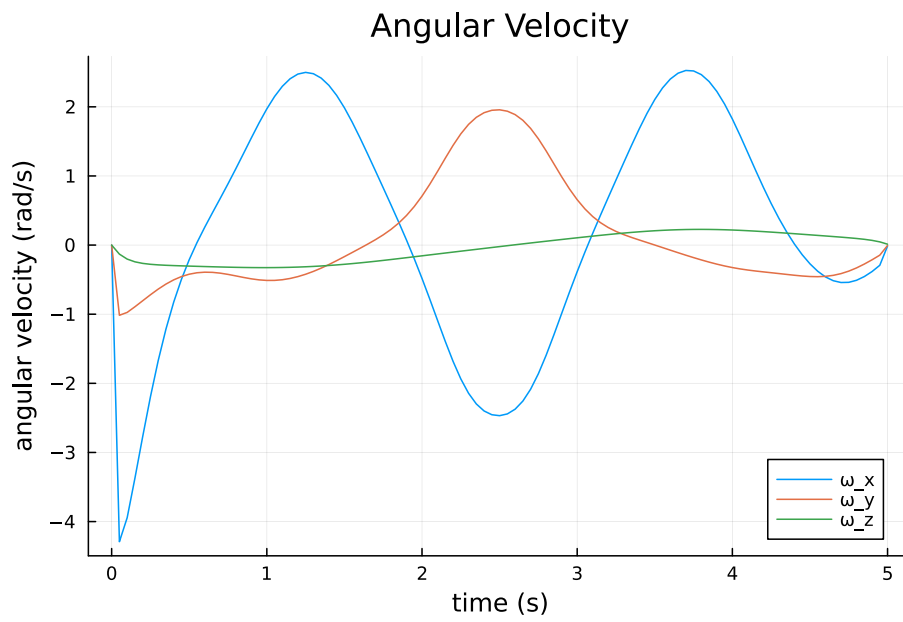
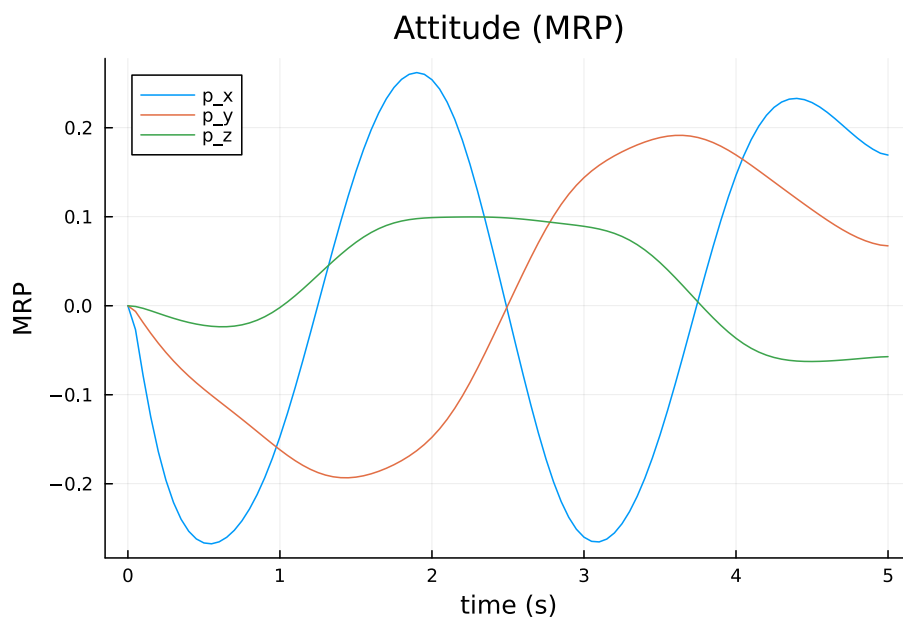
iter	J	ΔJ	d	α
1	3.013e+02	1.34e+05	2.81e+01	1.0000
2	1.078e+02	5.36e+02	1.34e+01	0.5000
3	4.906e+01	1.34e+02	4.72e+00	1.0000
4	4.429e+01	1.16e+01	2.44e+00	1.0000
5	4.402e+01	8.25e-01	2.54e-01	1.0000
6	4.398e+01	1.50e-01	8.84e-02	1.0000
7	4.396e+01	3.99e-02	7.50e-02	1.0000
8	4.396e+01	1.38e-02	3.90e-02	1.0000
9	4.396e+01	5.46e-03	3.32e-02	1.0000
10	4.396e+01	2.48e-03	2.03e-02	1.0000
11	4.396e+01	1.25e-03	1.69e-02	1.0000
12	4.395e+01	6.83e-04	1.14e-02	1.0000
13	4.395e+01	4.00e-04	9.37e-03	1.0000
14	4.395e+01	2.45e-04	6.94e-03	1.0000
15	4.395e+01	1.55e-04	5.66e-03	1.0000

Position



Velocity





```

[ Info: iLQR converged
[ @ Main c:\CMU\SEM II\OCRL\16745---Optimal-Control-and-Reinforcement-Learning---Spring-2025\HW3_S25\jl_notebook
_cell_df34fa98e69747e1a8f8a730347b8e2f_X21sZmlsZQ==.jl:43
[ Info: Listening on: 127.0.0.1:8702, thread id: 1
[ @ HTTP.Servers C:\Users\barat\.julia\packages\HTTP\4AUP\src\Servers.jl:382
[ Info: MeshCat server started. You can open the visualizer by visiting the following URL in your browser:
[ http://127.0.0.1:8702
[ @ MeshCat C:\Users\barat\.julia\packages\MeshCat\9QrxD\src\visualizer.jl:43
  
```

Test Summary: | Pass Total Time

ilqr | 1 1 35.6s

Test.DefaultTestSet("ilqr", Any[], 1, false, false, true, 1.742824473108e9, 1.742824508679e9, false, "c:\\CMU\\SEM II\\OCRL\\16745--Optimal-Control-and-Reinforcement-Learning--Spring-2025\\HW3_S25\\jl_notebook_cell_df34fa98e69747e1a8f8a730347b8e2f_X23sZmlsZQ==.jl")

Part B: Tracking solution with TVLQR (5 pts)

Here we will do the same thing we did in Q1 where we take a trajectory from a trajectory optimization solver, and track it with TVLQR to account for some model mismatch. In DIRCOL, we had to explicitly compute the TVLQR control gains, but in iLQR, we get these same gains out of the algorithm as the K's. Use these to track the quadrotor through this maneuver.

```
In [7]: @testset "iLQR with model error" begin

    # set verbose to false when you submit
    Xilqr, Uilqr, Kilqr, t_vec, params = solve_quadrotor_trajectory(verbose = false)

    # real model parameters for dynamics
    model_real = (mass=0.5,
                  J=Diagonal([0.0025, 0.002, 0.0045]),
                  gravity=[0,0,-9.81],
                  L=0.1550,
                  kf=0.9,
                  km=0.0365,dt = 0.05)

    # simulate closed loop system
    nx, nu, N = params.nx, params.nu, params.N
    Xsim = [zeros(nx) for i = 1:N]
    Usim = [zeros(nu) for i = 1:(N-1)]

    # initial condition
    Xsim[1] = 1*Xilqr[1]

    # TODO: simulate with closed loop control
    for i = 1:(N-1)
        Usim[i] = Uilqr[i] - Kilqr[i]*(Xsim[i] - Xilqr[i])
        Xsim[i+1] = rk4(model_real, quadrotor_dynamics, Xsim[i], Usim[i], model_real.dt)
    end

    # -----testing-----
    @test 1e-6 <= norm(Xilqr[50] - Xsim[50],Inf) <= .3
    @test 1e-6 <= norm(Xilqr[end] - Xsim[end],Inf) <= .3

    # -----plotting-----
    Xm = hcat(Xsim...)
    Um = hcat(Usim...)
    Xilqrm = hcat(Xilqr...)
    Uilqrm = hcat(Uilqr...)
    plot(t_vec,Xilqrm[1:3,:]',ls=:dash, label = "",lc = [:red :green :blue])
    display(plot!(t_vec,Xm[1:3,:]',title = "Position (-- is iLQR reference)",
```



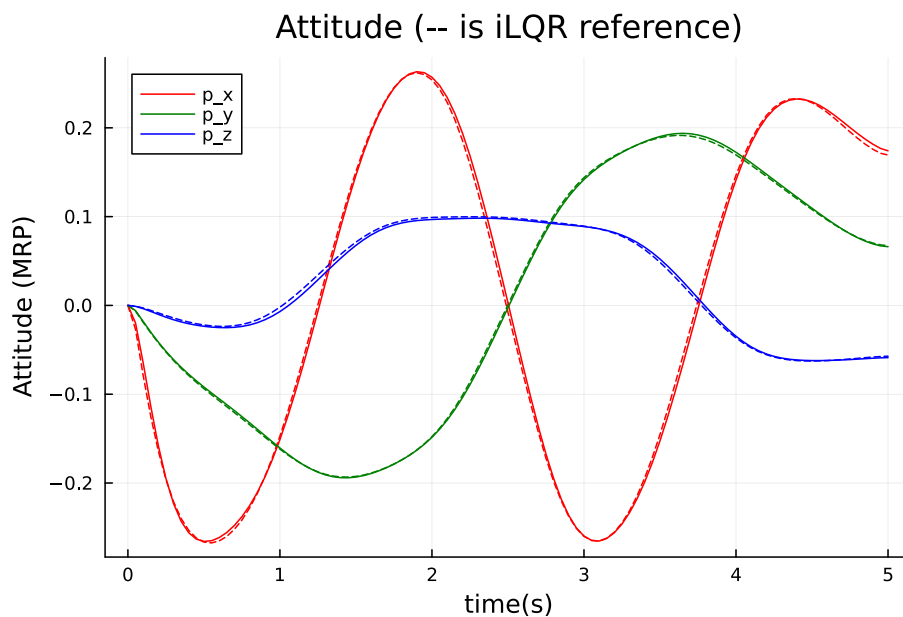
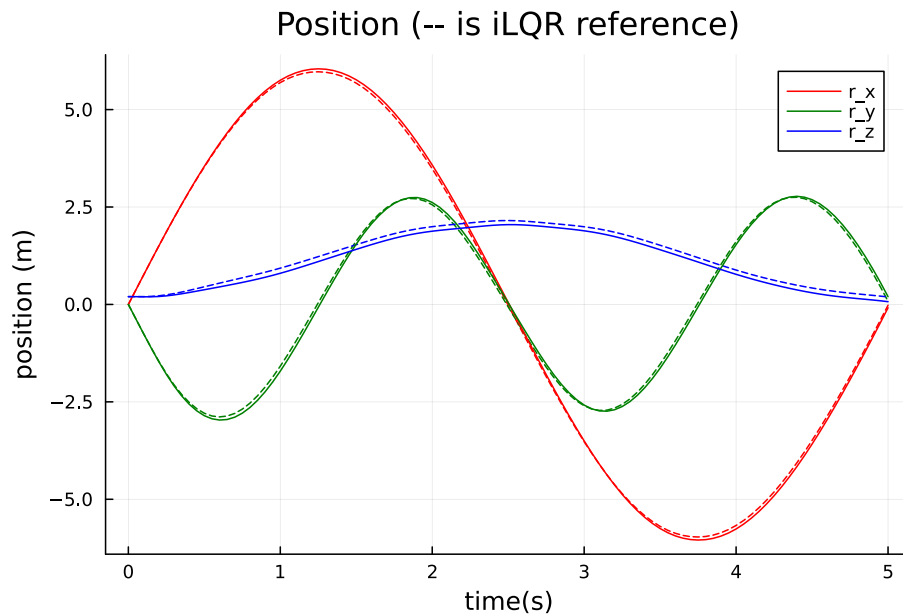
```

        xlabel = "time(s)", ylabel = "position (m)",
        label = ["r_x" "r_y" "r_z"],lc = [:red :green :blue]))

    plot(t_vec,Xilqrm[7:9,:]',ls=:dash, label = "",lc = [:red :green :blue])
    display(plot!(t_vec,Xm[7:9,:]',title = "Attitude (-- is iLQR reference)",
        xlabel = "time(s)", ylabel = "Attitude (MRP)",
        label = ["p_x" "p_y" "p_z"],lc = [:red :green :blue]))

    display(animate_quadrotor(Xilqr, params.Xref, params.model.dt))
end

```



```

┌ Info: Listening on: 127.0.0.1:8703, thread id: 1
└ @ HTTP.Servers C:\Users\barat\.julia\packages\HTTP\4AUPl\src\Servers.jl:382
┌ Info: MeshCat server started. You can open the visualizer by visiting the following URL in your browser:
└ http://127.0.0.1:8703
┌ @ MeshCat C:\Users\barat\.julia\packages\MeshCat\9QrxD\src\visualizer.jl:43

```

Test Summary: | Pass Total Time
iLQR with model error | 2 2 1.2s
Test.DefaultTestSet("iLQR with model error", Any[], 2, false, false, true, 1.74282450908e9, 1.742824510261e9, false, "c:\\CMU\\SEM II\\OCRL\\16745---Optimal-Control-and-Reinforcement-Learning---Spring-2025\\HW3_S25\\jl_notebook_cell_df34fa98e69747e1a8f8a730347b8e2f_X25sZmlsZQ==.jl")

Processing math: 100%