

In this project, I wrote a software that plans a trajectory for the end-effector of the youBot, an omnidirectional mobile robot with a 5-DOF robotic arm, performs an odometry as the chassis moves and performs feedback control to drive the robot in the desired trajectory. The simulated planned trajectory is demonstrated in CoppeliaSim.

### Milestone 1

Next\_State.py - computes the configuration of the robot in the next time step. The function inputs the current robot configuration and joint speeds. Given A 12-vector representing the current configuration of the robot, a 9-vector of controls indicating the arm and wheel twist, a timestep  $\Delta t$  and a speed limit, output a 12-vector representing the configuration of the robot time  $\Delta t$  later. The function uses first-order Euler integration to calculate wheel and joint angles at the next time step.

### Testing milestone 1:

To test the NextState function, I Simulated the following controls for 1 second and watch the results in the CoppeliaSim capstone scene.

max\_ang\_speed = 5

dt=0.01

Total time = 1 sec

Test 1: Driving the robot chassis forward

$u=[0, 0, 0, 0, 0, 10, 10, 10, 10]$

Test 2 : Sliding the robot chassis sideways

$u=[0, 0, 0, 0, 0, -10, 10, -10, 10]$

Test 3: Spinning the robot chassis in counterclockwise direction

$u=[0, 0, 0, 0, 0, -10, 10, 10, -10]$

**To run the file : python code/next\_state.py**

**The test results are in folder testing\_milestones\_results/milestone 1**

## **Milestone 2**

Trajectory\_Generator.py - generates the reference trajectory for the end-effector frame {e}. The function inputs the initial end-effector configuration, initial cube configuration, desired cube configuration, and number of configurations per second. The function outputs a matrix containing the end effector configuration at all time steps throughout the trajectory.

I am using gripper\_state as 0 = open

1 = close

The trajectory can be divided into smaller goals :

- Initial to standoff position
- Standoff position to grasp position
- Closing the gripper
- Grasp to standoff position
- Standoff to goal position
- From goal position to final position
- open the gripper
- From final position to standoff position

## **Testing milestone 2:**

total time of the motion in seconds=3

time-scaling method : considered fifth-order polynomial

no of points (Start and stop) in the discrete representation of the trajectory :

For driving : 500 points

For picking/dropping : 100 points

The number of trajectory reference configurations per 0.01 seconds i.e k=1

Input for the functions are :

The initial configuration of the end-effector in the reference trajectory: `Tse_initial = np.array([[0, 0, 1, 0], [0, 1, 0, 0], [-1, 0, 0, 0.5], [0, 0, 0, 1]])`

The cube's initial configuration: `Tsc_initial = np.array([[1, 0, 0, 1], [0, 1, 0, 0], [0, 0, 1, 0.025], [0, 0, 0, 1]])`

The cube's desired final configuration: `Tsc_goal = np.array([[0, 1, 0, 0], [-1, 0, 0, -1], [0, 0, 1, 0.025], [0, 0, 0, 1]])`

The end-effector's configuration relative to the cube when it is grasping the cube (the two frames located in the same coordinates, rotated about the y axis):

`Tce_grasp = np.array([[-1/np.sqrt(2), 0, 1/np.sqrt(2), 0], [0, 1, 0, 0], [-1/np.sqrt(2), 0, -1/np.sqrt(2), 0], [0, 0, 0, 1]])`

The end-effector's standoff configuration above the cube, before and after grasping, relative to the cube (the {e} frame located 0.1m above the {c} frame, rotated about the y axis):

`Tce_standoff = np.array([[-1/np.sqrt(2), 0, 1/np.sqrt(2), 0], [0, 1, 0, 0], [-1/np.sqrt(2), 0, -1/np.sqrt(2), 0.1], [0, 0, 0, 1]])`

**To run the file : `python code/generate_trajectory.py`**

**Results for the tests are in `testing_milestone_results/milestone 2`**

### Milestone 3

Feedback\_Control.py - calculates the kinematic task-space feedforward plus feedback control law.

$$V(t) = [Ad_{X^{-1}-X_d}]V_d(t) + K_p X_{err} + K_i \int_0^t X_{err}(t)dt$$

$$[V_d] = \frac{1}{\Delta t} \log(X^{-1}X_d)$$

$V$  is the calculated end-effector twist

$V_d$  is the reference twist

$X$  is the current end-effector configuration

$X_d$  is the desired end-effector configuration

$X_{err}$  is the error between the current end-effector configuration and the reference trajectory

$K_p$  is the proportional gain

$K_i$  is the integral gain

Once I calculated the end-effector twist, I needed to convert this to commanded wheel and arm joint speeds  $(u, \theta')$ . To do so, I used the pseudoinverse of the jacobian matrix:

$$(u, \theta') = J_e^+(\theta)V$$

### Testing milestone 3:

KP = 0

KI = 0

dt = 0.01

curr\_config = np.array([0, 0, 0, 0, 0, 0, 0.2, -1.6, 0, 0, 0, 0, 0, 0])

actual end-effector configuration

```
X = np.array([[0.170, 0, 0.985, 0.387],  
              [0, 1, 0, 0],  
              [-0.985, 0, 0.170, 0.570],  
              [0, 0, 0, 1]])
```

end-effector reference configuration

```
Xd = np.array([[0, 0, 1, 0.5],  
               [0, 1, 0, 0],  
               [-1, 0, 0, 0.5],  
               [0, 0, 0, 1]])
```

end-effector reference configuration at the next timestep in the reference trajectory

```
Xd_next = np.array([[0, 0, 1, 0.6],  
                    [0, 1, 0, 0],  
                    [-1, 0, 1, 0.3],  
                    [0, 0, 0, 1]])
```

**To run the file : python code/feedback\_control.py**

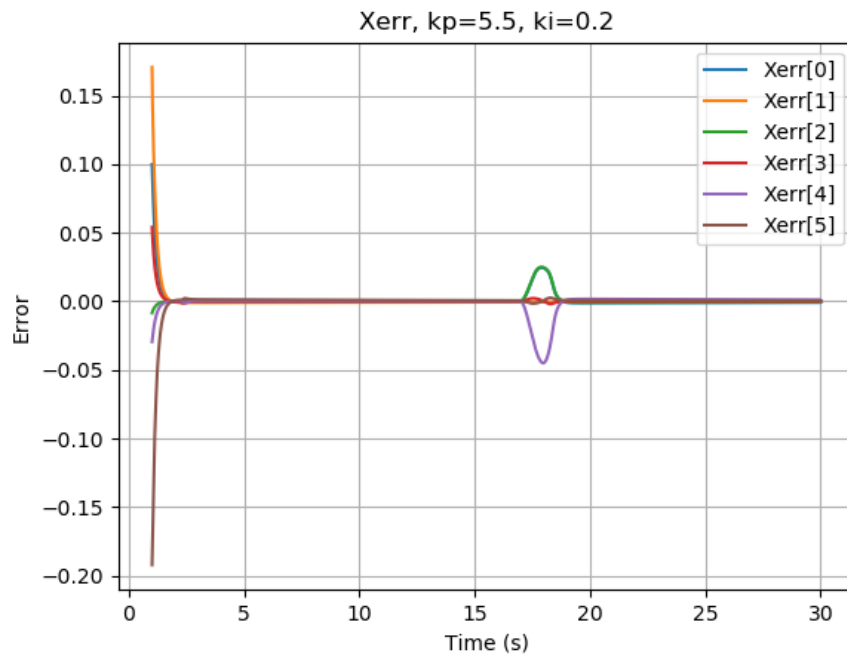
**Results for the tests are in testing\_milestone\_results/milestone 3**

**Full code** Python code generates a reference trajectory and uses a PI controller to follow the reference trajectory. Code outputs a csv file containing robotic configuration at each time step .

The results for this project can be split into 3 categories:

1.)Best : Planning and executing a motion without overshoot or steady-state error.

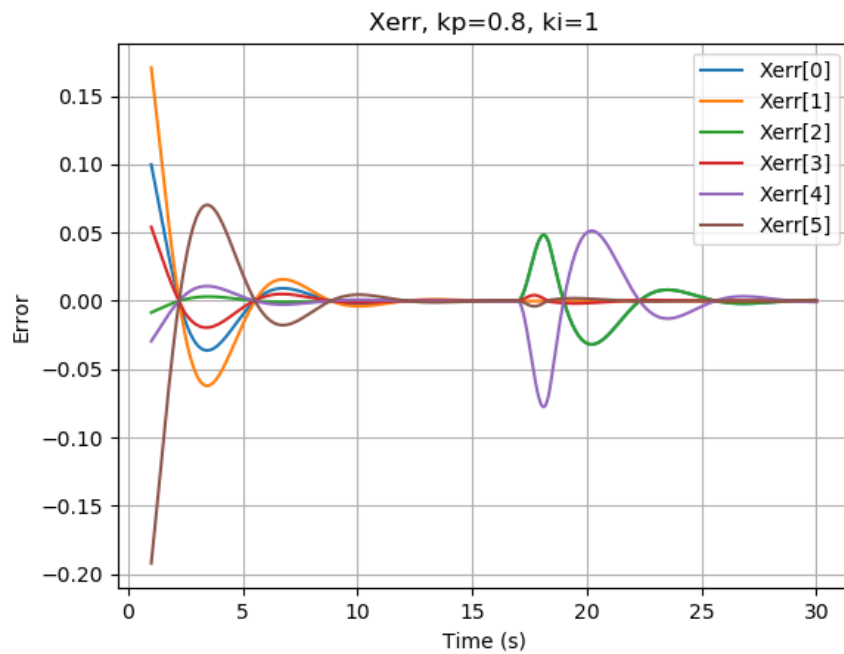
PI controller with feedback gains of  $K_p = 5.5$  and  $K_i = 0.2$



We can see that there is no overshoot, no steady-state error, and fast settling time with a little bump in between after which the plot PI again converges to 0

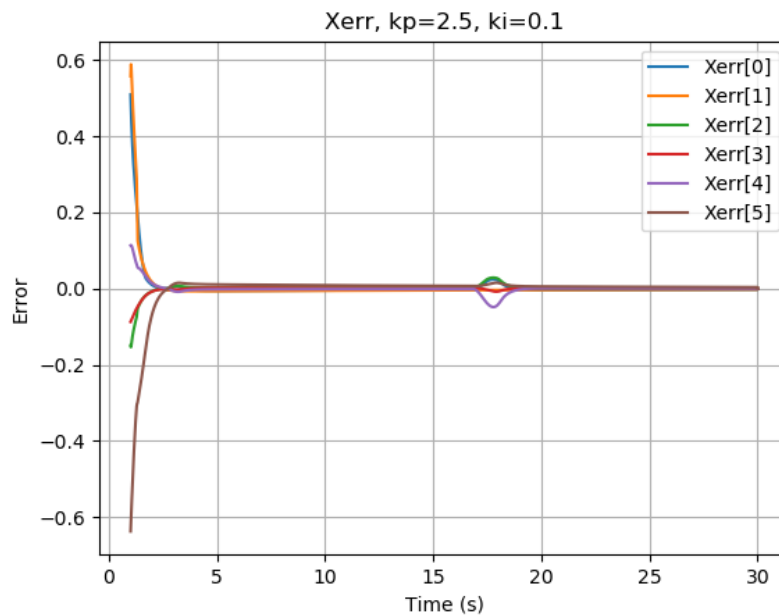
2.)Overshoot - Planning and executing a motion with overshoot but without steady-state error.

PI controller with feedback gains of  $K_p = 0.8$  and  $K_i = 1$



From the plot we can observe that there is an overshoot at the beginning of the motion and when there is a bump in between. The plot converges with no steady-state error

3.) NewTast results - Planning and executing the trajectory with different start and finish configuration and  $K_p=2.5$  ,  $K_i=0.1$



We can see that there is no overshoot, no steady-state error, and fast settling time with a little bump in between after which the plot PI again converges to 0

Additional :

**Implementation of singularity avoidance :** The tolerance option allows you to specify how close to zero a singular value must be to be treated as zero.

Tolerance =  $1e-3$  added in Pinv : `Je_inv = np.linalg.pinv(Je, rcond=1e-3)`

Where rcond is used to zero out small entries in a diagonal matrix with positive real values (singular values)

By treating small singular values (that are greater than the default tolerance) as zero, I want to avoid having pseudoinverse matrices with unreasonably large entries

**Implementation of self-collision avoidance**



My testJointLimits function is checking for Joint 3 and Joint 4

I check joint limit before calculating Jacobian .If the joint value is higher than the joint limit , I make the column of that joint in Jacobian 0

After implementing the self-collision, controller values need to be further tuned to work properly .That is why the self-collision implementation code is commented out

