

Homework 1

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Frames are defined at the tip of each link with one extra (first) frame defined as fixed base of the robot. So for a manipulator with n joints, there are $n+1$ frames with $n+1^{\text{th}}$ frame as end effector. Pose of end effector is defined as $\mathbf{p}: [\mathbf{x}, \mathbf{y}, \mathbf{z}, \mathbf{q0}, \mathbf{q1}, \mathbf{q2}, \mathbf{q3}]$.

Euler angles at each joint j_i are used to find homogenous transformation of frame (i) and frame (i+1) as follows:

$$H_{i+1}^i = \begin{bmatrix} R_{i+1}^i & R_{i+1}^i * [0] \\ 0 & 1 \end{bmatrix} \begin{matrix} l_i \\ 0 \end{matrix}$$

Vector \mathbf{x} is defined as a stack of [roll angles; pitch angles; yaw angles];

Given a target position of end effector, x_d , the inverse kinematics is done as a search for joint angles that minimizes the **cost**: $(p_d - p)^T Q (p_d - p) + w^* (\text{deviation from joint limits})^{-1}$

MATLAB function **fmincon** was used to carry on the optimization.

Joint limits are additionally modelled as hard constrained by putting the bounds in fmincon arguments.

Obstacles were modelled as non-linear constraints (number of links X number of obstacles). The constraint is calculated by solving the equation of each link as line segment with each sphere. The constraints are modelled as hard inequalities and passed into fmincon argument.

Part 1. The results of optimization/ inverse kinematics are as:

| | | | | | | | | |
|---------------------|------------|---------|-------|-------|-------|-------|-------|-------|
| | target | 3.000 | 3.000 | 2.000 | 0.707 | 0.408 | 0.408 | 0.408 |
| Without gradient | position 1 | 3.007 | 3.000 | 2.013 | 0.708 | 0.391 | 0.431 | 0.400 |
| | error 1 | 0.0235% | | | | | | |
| | run time 1 | 111.03 | | | | | | |

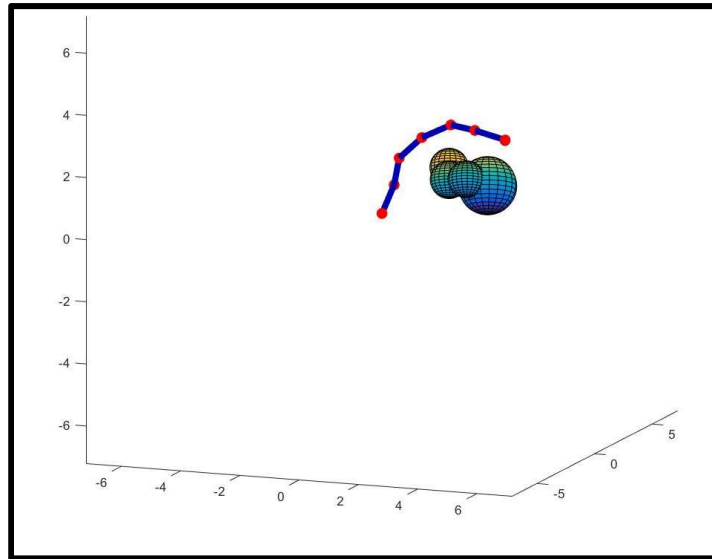


Figure 1: final pose of the robot without including gradient in the optimizer

Part 2. In this part, gradient of cost was calculated with respect to each joint angles and included into the optimizer, fmincon. Upon several unsuccessful attempts on using standard automatic differentiation toolboxes (failed due to constraint on input argument type), I finally wrote a small code to find gradient using “forward finite difference” approach: calculate the delta changes in end effector pose upon forward perturbation of one joint angles at a time.

The results of optimization/ inverse kinematics are as:

| | | | | | | | | |
|---|------------|---------|-------|-------|-------|-------|-------|-------|
| | target | 3.000 | 3.000 | 2.000 | 0.707 | 0.408 | 0.408 | 0.408 |
| With Gradient - "interior -point" | position 2 | 3.005 | 2.988 | 2.057 | 0.720 | 0.336 | 0.453 | 0.405 |
| | error 2 | 0.2245% | | | | | | |
| | run time 2 | 12.88 | | | | | | |

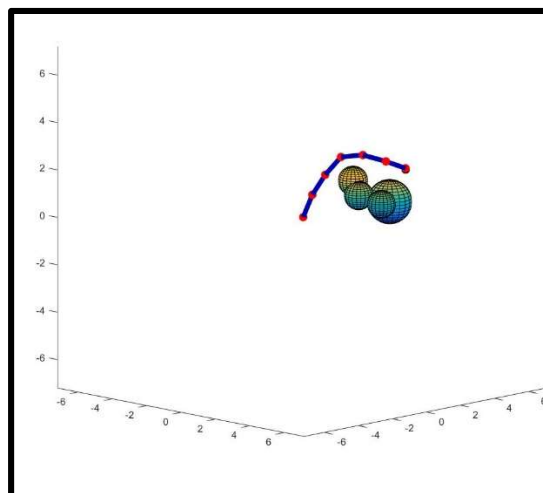


Figure 2: final pose of manipulator after including gradient in the optimizer and using "active-set" Algorithm in fmincon

Few trials were conducted to compare the results with and without including gradient.

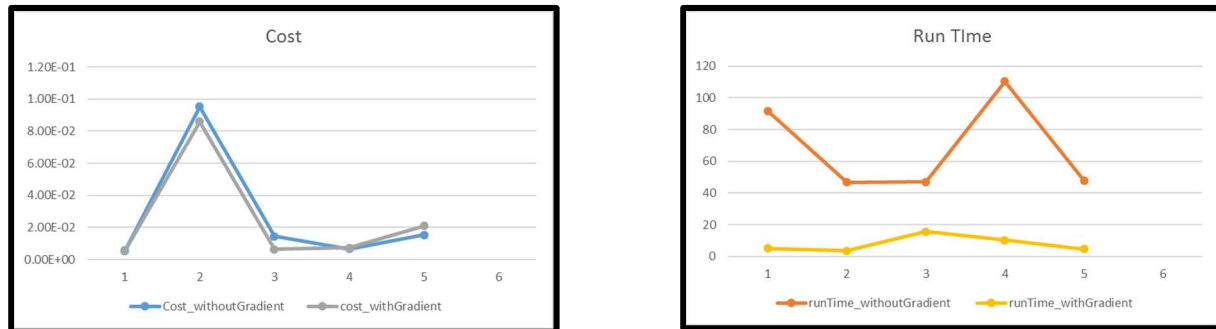


Figure 3: comparison of cost and run time between optimizer without and with gradient

Although the cost is similar in two cases, the run time has significantly come down.

Part 3. In this part, a new optimizer is explored, CMA-ES (*Covariance Matrix Adaptation Evolution Strategy*). The optimizer is taken from internet and remains unchanged except decreasing the number of MaxIterations.

CAMES also takes lower and upper bounds as hard constraints but other inequalities were modelled inside the cost function. The cost function now returns NaN whenever the constraints related to obstacles avoidance get violated. This works well as the optimizer will just ignore those points.

The results of optimization/ inverse kinematics including the comparison table with different algorithms inside fmincon are shown below:

| | | | | | | | | |
|----------------|------------|---------------|-------|-------|-------|-------|-------|-------|
| | target | 3.000 | 3.000 | 2.000 | 0.707 | 0.408 | 0.408 | 0.408 |
| CMAES | position 3 | 3.017 | 3.006 | 1.989 | 0.696 | 0.416 | 0.377 | 0.447 |
| | error 3 | 0.0646% | | | | | | |
| | run time 3 | 94.28 | | | | | | |
| interior-point | position 2 | 3.005 | 2.988 | 2.057 | 0.720 | 0.336 | 0.453 | 0.405 |
| | error 2 | 0.2245% | | | | | | |
| | run time 2 | 12.88 | | | | | | |
| SQP | position 3 | 3.002 | 3.001 | 2.001 | 0.708 | 0.406 | 0.413 | 0.405 |
| | error 3 | 0.000864% | | | | | | |
| | run time 3 | 3.10 | | | | | | |
| active-set | position 3 | 3.000 | 3.000 | 2.000 | 0.707 | 0.408 | 0.408 | 0.408 |
| | error 3 | 0.0000000513% | | | | | | |
| | run time 3 | 3.06 | | | | | | |

Although cmaes gave better results in terms of reducing the relative error by 1 order, it did not do that well in terms of run time. Also, it was observed that increasing the bound on Max Iterations improves the error further but at a big expense of run time cost.

The best results were found while using “Active-Set” algorithm inside fmincon.

The order of performance in terms of run time was observed as:

Active Set > SQP > Interior Point > CMAES > Interior Point (excluding Gradient)

The order of performance in terms of accuracy was observed as:

Active Set > SQP > CMAES ~ Interior Point (excluding Gradient) > Interior Point

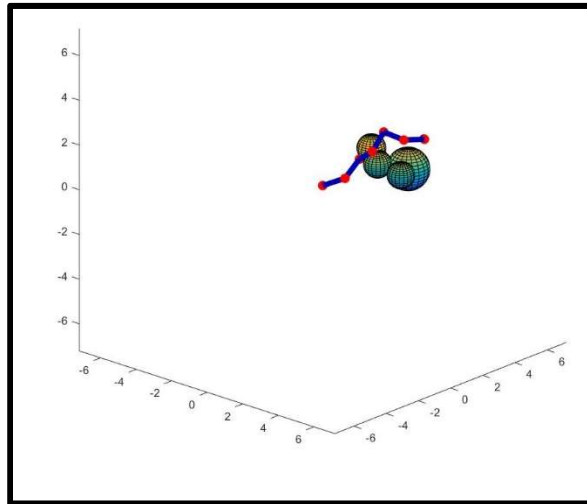


Figure 4: final robot pose using CMAES

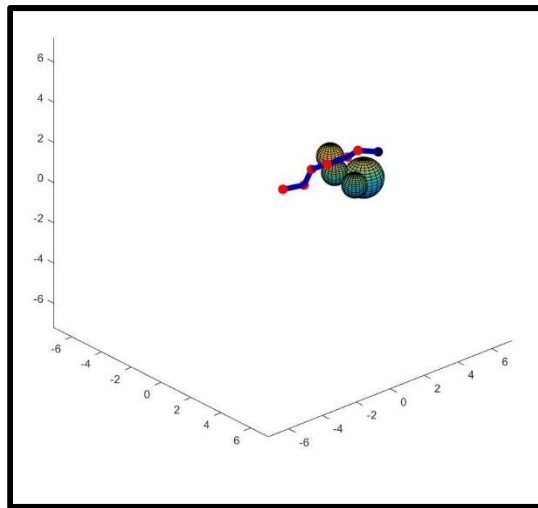


Figure 5: Final robot pose using "active-set" Algorithm in fmincon

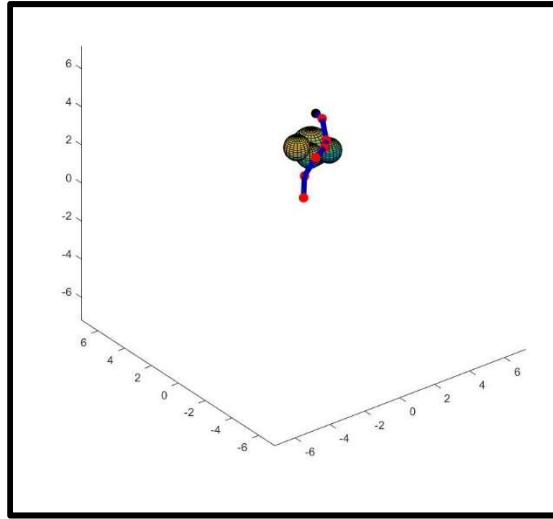


Figure 6: Final robot pose using "SQP" algorithm in fmincon

Part 4. In this part, the fmincon was used with "active-set" algorithm to catch all the local minimum that comes while the optimizer is running. The local minimas with decreasing cost points (left to right) are as:

| | set 1 | set 2 | set 3 | set 4 | set 5 | set 6 |
|----------|----------|----------|----------|----------|----------|----------|
| cost | 0.057445 | 0.02809 | 0.017828 | 0.010118 | 0.005075 | 0.001787 |
| r1 (deg) | 11.49792 | 10.34167 | 11.24301 | 11.7638 | 11.53658 | 12.3193 |
| r2 (deg) | 21.75383 | 21.90032 | 23.69133 | 21.719 | 22.10394 | 22.55699 |
| r3 (deg) | 30.17478 | 31.81528 | 31.04233 | 32.04301 | 33.31883 | 35.28631 |
| r4 (deg) | 36.06649 | 36.59041 | 32.81675 | 34.1792 | 32.55745 | 30.40239 |
| r5 (deg) | 50.37528 | 51.92784 | 53.17439 | 51.81438 | 51.55295 | 51.10728 |
| r6 (deg) | 50.70236 | 47.3133 | 47.89691 | 45.83603 | 47.79836 | 48.27633 |
| p1 (deg) | 51.66504 | 55.22651 | 51.31115 | 51.85024 | 50.55845 | 49.15293 |
| p2 (deg) | 59.52149 | 58.11626 | 55.24543 | 54.86866 | 54.3456 | 53.10545 |
| p3 (deg) | 66.67028 | 63.41623 | 60.40981 | 64.30647 | 61.78014 | 60.00572 |
| p4 (deg) | 68.46077 | 66.10622 | 67.76618 | 69.64268 | 68.00642 | 67.48325 |
| p5 (deg) | 68.48818 | 65.38836 | 69.36519 | 68.79414 | 69.83116 | 71.68023 |
| p6 (deg) | 68.81147 | 67.88147 | 67.14503 | 66.83959 | 67.43816 | 67.40812 |
| y1 (deg) | 73.6793 | 71.91129 | 75.48768 | 71.77261 | 71.62646 | 70.93161 |
| y2 (deg) | 81.34203 | 82.79342 | 84.44238 | 82.25654 | 83.7536 | 84.63876 |
| y3 (deg) | 87.04177 | 85.16859 | 87.60818 | 91.15016 | 93.14556 | 96.45088 |
| y4 (deg) | 114.1434 | 113.422 | 113.1507 | 112.5001 | 112.3426 | 111.3539 |
| y5 (deg) | 120.4935 | 118.8234 | 119.915 | 121.3517 | 120.7795 | 121.2109 |
| y6 (deg) | 141.6468 | 138.1486 | 136.471 | 139.4983 | 137.7669 | 136.0691 |

For the similar accuracy, there is a variation of up to 10 degrees in joint angles. Depending on the requirement, we can make use of these local minimas instead of disposing them off during optimization.

Learning:

- FMINCON is a powerful and vast toolbox. It can be used for number of applications and depending on options chosen, user can optimize on accuracy and performance.
- CMAES: More study is required in this domain to understand the tool and concept better. In limited time, a standard tool was used without understanding the operation of this technique. A new method of returning NaN in cost function was identified to incorporate inequalities in CMAES. Finally, this technique is being used in all parts of the problem set.
- A lot of **automatic differentiation** toolboxes were explored for eg. AutoDiff in MATLAB library. Due to **specific input argument** type requirement, I was not able to use them for my application. Instead, finite difference approach was used to calculate gradient.