

Inverse Kinematics of 6R Manipulator by Newton's Method

November 23, 2022

Newton's Method (Example)

Task: find a root of $f(x) = x^2 - 2$

Given: starting point $x_0 = 1$, number of steps $m = 3$, tolerance $e = 10^{-5}$

Newton's step:

$$x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)}$$

Steps:

$$x_1 = x_0 - \frac{f(x_0)}{f'(x_0)} = 1 - \frac{-1}{2 \cdot 1} = 1.5$$

$$x_2 = 1.5 - \frac{0.25}{3} = 1.416667$$

$$x_3 = \dots = 1.414216$$

The norm $\|f(x_3)\| = 6 \cdot 10^{-6} \leq e \Rightarrow x_3$ is a good approximation of a root

Newton's Method (Algorithm)

Algorithm 1: Newton's Method

Input: $\mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}), \dots, f_s(\mathbf{x}))$, $\mathbf{x}_0 \in \mathbb{R}^n$, $m \in \mathbb{R}$, $e \in \mathbb{R}_+$

Output: (s, \mathbf{x}^*) , where s denotes the state of convergence and $\mathbf{x}^* \in \mathbb{R}^n$.

If the algorithm converged in m steps with tolerance e , then $s = \text{True}$ and \mathbf{x}^* is the approximated solution. Otherwise, $s = \text{False}$ and \mathbf{x}^* is the point obtained in the last iteration.

```
1  $\mathbf{x}^* \leftarrow \mathbf{x}_0$ 
2 for (  $k \leftarrow 0$ ;  $k < m$ ;  $k \leftarrow k + 1$  )
3   if  $\|\mathbf{f}(\mathbf{x}^*)\| \leq e$  then
4     return (True,  $\mathbf{x}^*$ )
5      $\mathbf{J} \leftarrow \left. \frac{\partial \mathbf{f}}{\partial \mathbf{x}} \right|_{\mathbf{x}^*}$ 
6      $\mathbf{x}^* \leftarrow \mathbf{x}^* - \mathbf{J}^+ \mathbf{f}(\mathbf{x}^*)$ 
7 return (False,  $\mathbf{x}^*$ )
```

Equations for \mathbf{R}_e and \mathbf{t}_e

$$\mathbf{M}_e = \mathbf{M}_1^0 \mathbf{M}_2^1 \mathbf{M}_3^2 \mathbf{M}_4^3 \mathbf{M}_5^4 \mathbf{M}_6^5$$

$$\underbrace{\begin{bmatrix} \mathbf{R}_e & \mathbf{t}_e \\ \mathbf{0}^\top & 1 \end{bmatrix}}_{\text{pose of the end effector}} = \prod_{i=1}^6 \mathbf{M}_i^{i-1}(\theta_i + \underbrace{\theta_{i,\text{offset}}, d_i, a_i, \alpha_i}_{\text{DH parameters}})$$

Hence,

$$\mathbf{R}_e = \underbrace{\prod_{i=1}^6 \mathbf{R}_i^{i-1}(\theta_i)}_{\mathbf{R}(\boldsymbol{\theta})}, \quad \bar{\mathbf{t}}_e = \begin{bmatrix} \mathbf{t}_e \\ 1 \end{bmatrix} = \underbrace{\prod_{i=1}^6 \mathbf{M}_i^{i-1}(\theta_i)}_{\bar{\mathbf{t}}(\boldsymbol{\theta}) = \begin{bmatrix} \mathbf{t}(\boldsymbol{\theta}) \\ 1 \end{bmatrix}} \begin{bmatrix} \mathbf{0} \\ 1 \end{bmatrix},$$

where $\boldsymbol{\theta} = (\theta_1, \dots, \theta_6)$.

The IKT equations are:

$$\mathbf{f}(\boldsymbol{\theta}) = \begin{bmatrix} \text{vec}(\mathbf{R}(\boldsymbol{\theta}) - \mathbf{R}_e) \\ \mathbf{t}(\boldsymbol{\theta}) - \mathbf{t}_e \end{bmatrix} = \mathbf{0}$$

where

$$\text{vec}(\mathbf{R}) = [r_{11} \quad r_{21} \quad r_{31} \quad r_{12} \quad r_{22} \quad r_{32} \quad r_{13} \quad r_{23} \quad r_{33}]^T$$

The Jacobian is:

$$\mathbf{J}(\boldsymbol{\theta}) = \frac{\partial \mathbf{f}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} = \begin{bmatrix} \frac{\partial \text{vec}(\mathbf{R}(\boldsymbol{\theta}))}{\partial \boldsymbol{\theta}} \\ \frac{\partial \mathbf{t}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \end{bmatrix} \in C(\boldsymbol{\theta}, \mathbb{R})^{12 \times 6}$$

since \mathbf{R}_e and \mathbf{t}_e are fixed and don't depend on $\boldsymbol{\theta}$.

By taking partial derivative of $\mathbf{R}(\boldsymbol{\theta})$ w.r.t. θ_k we get:

$$\frac{\partial \mathbf{R}(\boldsymbol{\theta})}{\partial \theta_k} = \prod_{i=1}^{k-1} \mathbf{R}_i^{i-1}(\theta_i) \cdot \frac{\partial \mathbf{R}_k^{k-1}(\theta_k)}{\partial \theta_k} \cdot \prod_{i=k+1}^6 \mathbf{R}_i^{i-1}(\theta_i) \in C(\boldsymbol{\theta}, \mathbb{R})^{3 \times 3}$$

By taking partial derivative of $\bar{\mathbf{t}}(\boldsymbol{\theta})$ w.r.t. θ_k we get:

$$\frac{\partial \bar{\mathbf{t}}(\boldsymbol{\theta})}{\partial \theta_k} = \prod_{i=1}^{k-1} \mathbf{M}_i^{i-1}(\theta_i) \cdot \frac{\partial \mathbf{M}_k^{k-1}(\theta_k)}{\partial \theta_k} \cdot \prod_{i=k+1}^6 \mathbf{M}_i^{i-1}(\theta_i) \begin{bmatrix} \mathbf{0} \\ 1 \end{bmatrix} \in C(\boldsymbol{\theta}, \mathbb{R})^4$$