

Kinematics

Prof. Darius Burschka

Technische Universität München
Institut für Informatik
Machine Vision and Perception Group (I6)

Objectives

- Understand basic concepts of inverse kinematics
- Understand the concept of workspace
- Compute inverse kinematics of simple robot manipulators using analytic methods
- Compute the inverse kinematics of complex robot manipulators using numeric methods

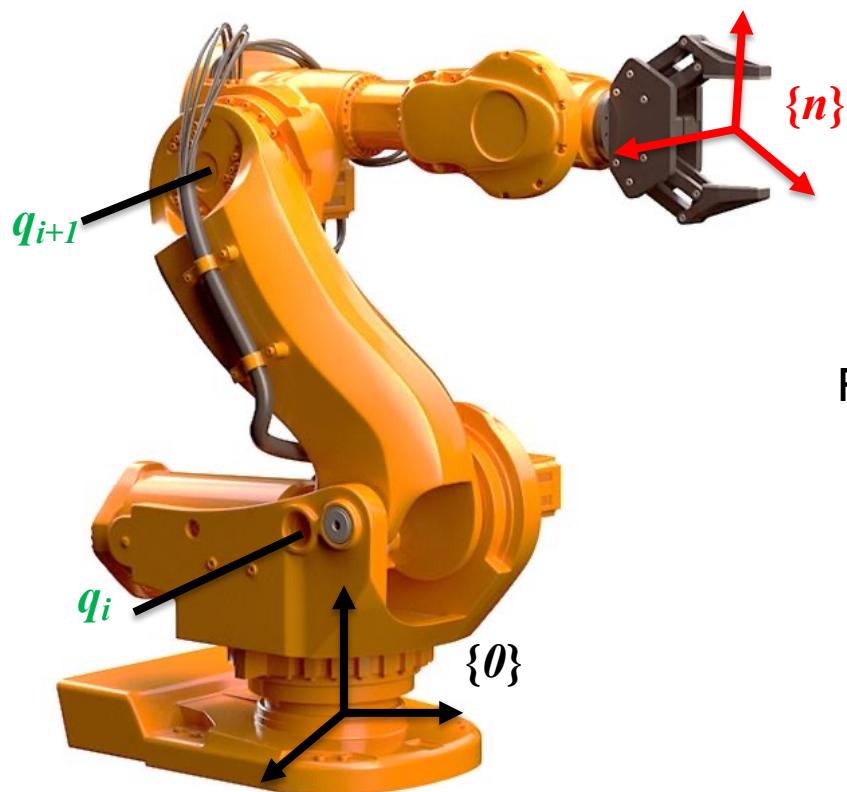
Outline

I. Introduction

2. Workspace (and existence of solutions)
3. Multiplicity of solutions
4. Analytic solutions
5. Numeric solutions
6. Numeric computation of the Jacobian

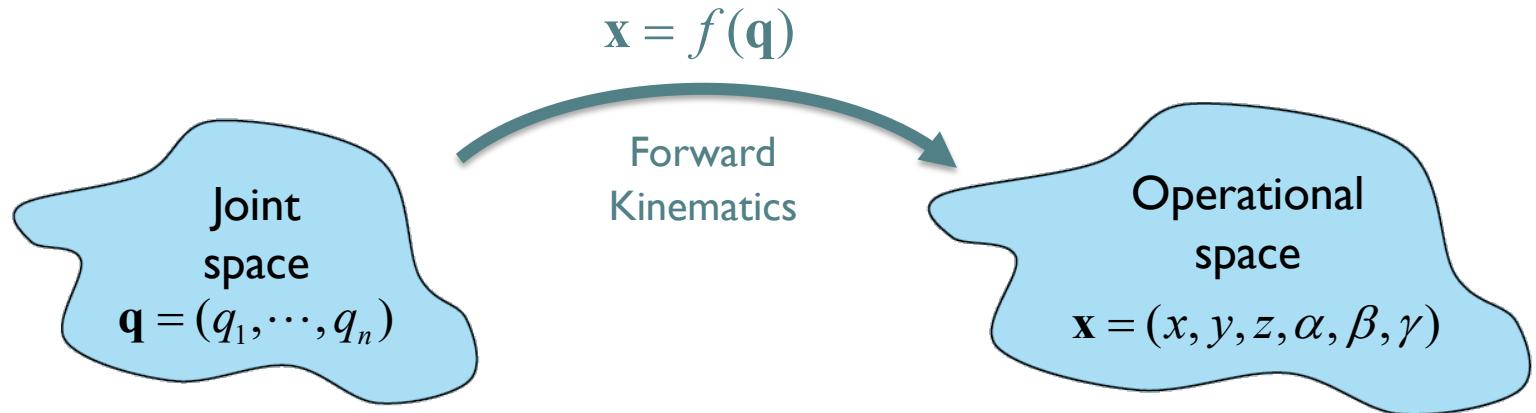
- Inverse Kinematics of Robot Manipulators -

Kinematics of Robot Manipulators



Relation between **joints** (q_i) and the **pose** (position/orientation) of some point (e.g.: frame $\{n\}$)

Kinematics of Robot Manipulators



- Forward kinematics

Given a joint configuration, find the pose (position/orientation) of some part of the robot Given $\mathbf{q} = (q_1, \dots, q_n)$

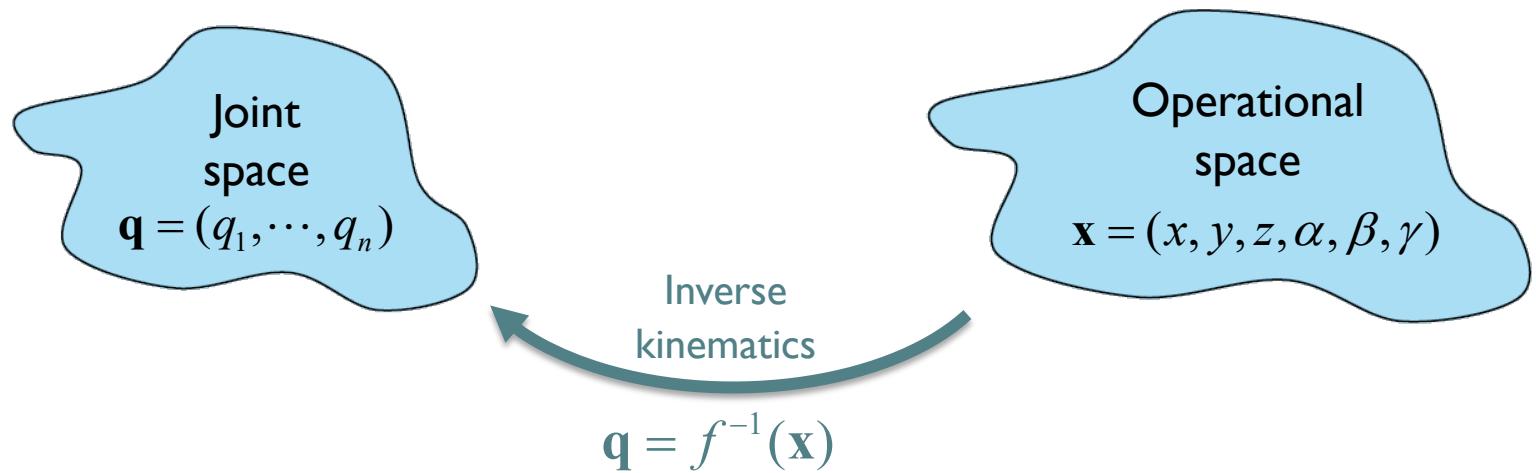
Find

$${}^0 T_{\mathbf{q}}(\mathbf{q})$$

$$\mathbf{x} = f(\mathbf{q})$$

For example: $\mathbf{x} = (x, y, z, \alpha, \beta, \gamma)$

Kinematics of Robot Manipulators



- Inverse kinematics

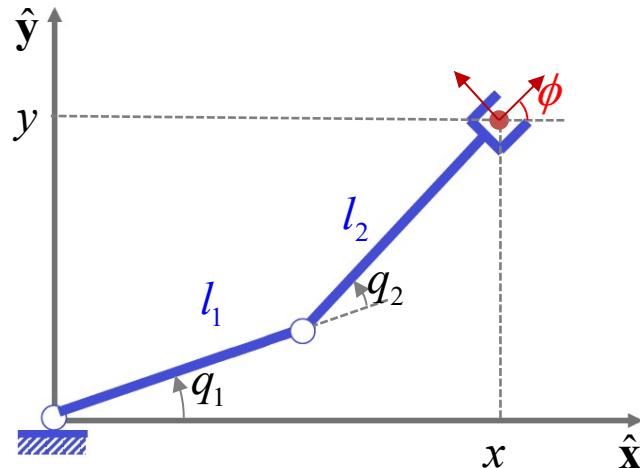
Given ${}^0T_n(\mathbf{q})$ or $\mathbf{x} = f(\mathbf{q})$ for some point of the robot (e.g. end effector)

Find $\mathbf{q} = (q_1, \dots, q_n)$

Kinematics of Robot Manipulators

Example: R-R Robot

- Position of a 2 dof robot



Cartesian variables

$$\mathbf{x} = \begin{bmatrix} x \\ y \end{bmatrix}$$

Considering only position

Joint variables

$$\mathbf{q} = \begin{bmatrix} q_1 \\ q_2 \end{bmatrix}$$

Forward kinematics

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} l_1 \cos(q_1) + l_2 \cos(q_1 + q_2) \\ l_1 \sin(q_1) + l_2 \sin(q_1 + q_2) \end{bmatrix}$$



$$\mathbf{x} = f(\mathbf{q})$$

Given \mathbf{q} , there exists a single \mathbf{x}

Inverse kinematics

$$\begin{bmatrix} q_1 \\ q_2 \end{bmatrix} = \begin{bmatrix} ? \\ ? \end{bmatrix}$$



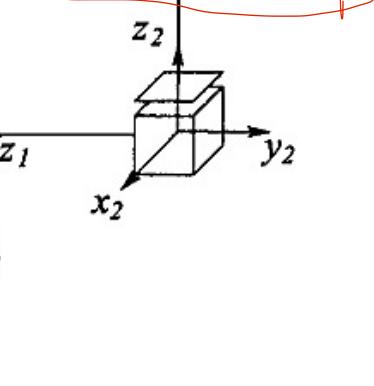
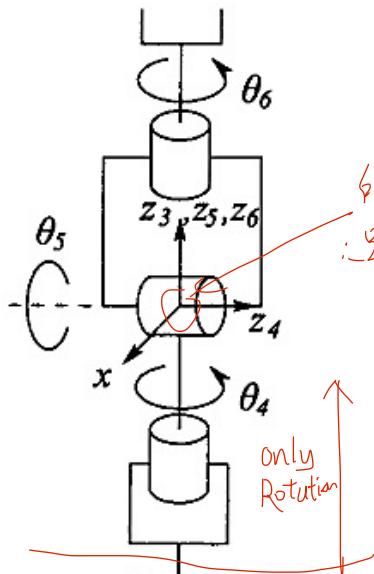
$$\mathbf{q} = f^{-1}(\mathbf{x}) = ?$$

Given \mathbf{x} , does there exist (a single) \mathbf{q} ?

Kinematics of Robot Manipulators

Example: Forward Kinematics

End effector with respect to the base:



Stanford Manipulator

$$T_6^0 = \begin{bmatrix} r_{11} & r_{12} & r_{13} & d_x \\ r_{21} & r_{22} & r_{23} & d_y \\ r_{31} & r_{32} & r_{33} & d_z \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Position and Orientation

where:

$$\begin{aligned}
 r_{11} &= c_1[c_2(c_4c_5c_6 - s_4s_6) - s_2s_5c_6] - d_2(s_4c_5c_6 + c_4s_6) \\
 r_{21} &= s_1[c_2(c_4c_5c_6 - s_4s_6) - s_2s_5c_6] + c_1(s_4c_5c_6 + c_4s_6) \\
 r_{31} &= -s_2(c_4c_5c_6 - s_4s_6) - c_2s_5c_6 \\
 r_{12} &= c_1[-c_2(c_4c_5s_6 + s_4c_6) + s_2s_5s_6] - s_1(-s_4c_5s_6 + c_4c_6) \\
 r_{22} &= -s_1[-c_2(c_4c_5s_6 + s_4c_6) + s_2s_5s_6] + c_1(-s_4c_5s_6 + c_4c_6) \\
 r_{32} &= s_2(c_4c_5s_6 + s_4c_6) + c_2s_5s_6 \\
 r_{13} &= c_1(c_2c_4s_5 + s_2c_5) - s_1s_4s_5 \\
 r_{23} &= s_1(c_2c_4s_5 + s_2c_5) + c_1s_4s_5 \\
 r_{33} &= -s_2c_4s_5 + c_2c_5 \\
 d_x &= c_1s_2d_3 - s_1d_2 + d_6(c_1c_2c_4s_5 + c_1c_5s_2 - s_1s_4s_5) \\
 d_y &= s_1s_2d_3 + c_1d_2 + d_6(c_1s_4s_5 + c_2c_4s_1s_5 + c_5s_1s_2) \\
 d_z &= c_2d_3 + d_6(c_2c_5 - c_4s_2s_5)
 \end{aligned}$$

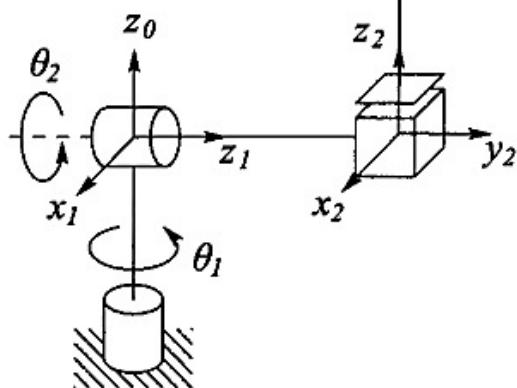
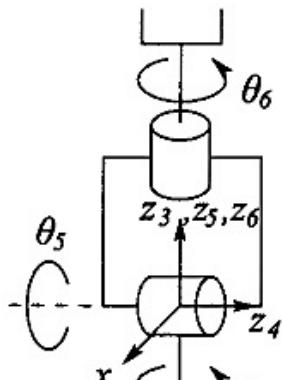
Kinematics of Robot Manipulators

Example: Inverse Kinematics

Compute the angles that achieve the following pose for the end effector:

$$T_6^0 = \begin{bmatrix} 0 & 1 & 0 & -0.154 \\ 0 & 0 & 1 & 0.763 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Numeric matrix



Stanford Manipulator

Equivalently, solve the following system:

$$c_1[c_2(c_4c_5c_6 - s_4s_6) - s_2s_5c_6] - s_1(s_4c_5c_6 + c_4s_6) = 0$$

$$s_1[c_2(c_4c_5c_6 - s_4s_6) - s_2s_5c_6] + c_1(s_4c_5c_6 + c_4s_6) = 0$$

$$-s_2(c_4c_5c_6 - s_4s_6) - c_2s_5c_6 = 1$$

$$c_1[-c_2(c_4c_5s_6 + s_4c_6) + s_2s_5s_6] - s_1(-s_4c_5s_6 + c_4c_6) = 1$$

$$s_1[-c_2(c_4c_5s_6 + s_4c_6) + s_2s_5s_6] + c_1(-s_4c_5s_6 + c_4c_6) = 0$$

$$s_2(c_4c_5s_6 + s_4c_6) + c_2s_5s_6 = 0$$

$$c_1(c_2c_4s_5 + s_2c_5) - s_1s_4s_5 = 0$$

$$s_1(c_2c_4s_5 + s_2c_5) + c_1s_4s_5 = 1$$

$$-s_2c_4s_5 + c_2c_5 = 0$$

System of nonlinear trigonometric equations!

非线性三角方程组!

$$c_1s_2d_3 - s_1d_2 + d_6(c_1c_2c_4s_5 + c_1c_5s_2 - s_1s_4s_5) = -0.154$$

$$s_1s_2d_3 + c_1d_2 + d_6(c_1s_4s_5 + c_2c_4s_1s_5 + c_5s_1s_2) = 0.763$$

$$c_2d_3 + d_6(c_2c_5 - c_4s_2s_5) = 0$$

Inverse Kinematics

- Find the joint angles

$$\mathbf{q} = f^{-1}(\mathbf{x})$$

Given a desired position and orientation for the end effector, find the joint angles

- It is a **synthesis** problem
- The input data (position and orientation) are of the form:

$$T = \begin{bmatrix} R & t \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Classical formulation:

Inverse kinematics for the end effector

$$\mathbf{x} = \begin{bmatrix} \mathbf{x}_p \\ \mathbf{x}_r \end{bmatrix}$$

Generalized formulation:

Inverse kinematics for task variables

- It is a nonlinear problem:

- Is there a solution?
- Is there a unique solution, or multiple solutions?
- How to solve it?



Answer: workspace,
redundancy

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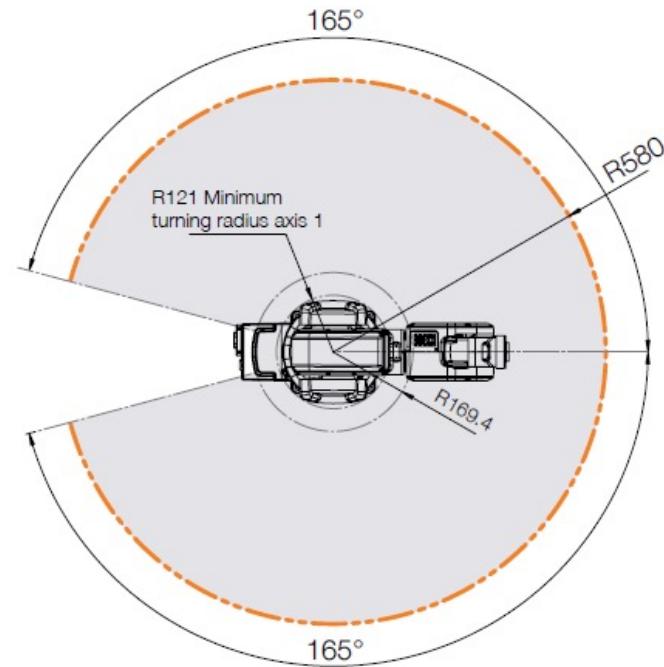
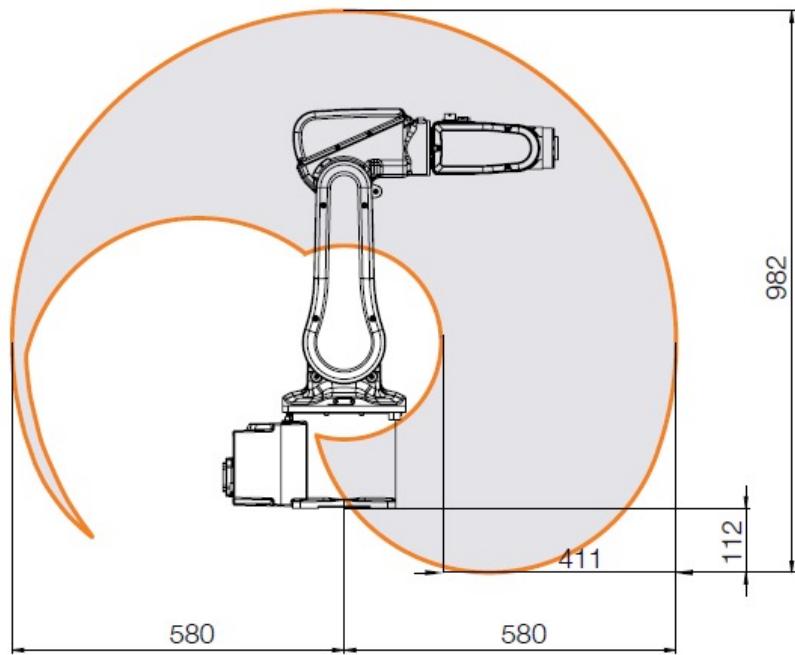
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- Inverse Kinematics of Robot Manipulators -

Prof. Oscar E. Ramos, Ph.D.

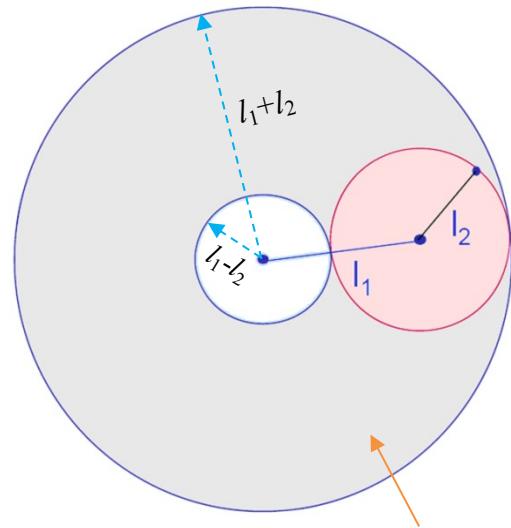
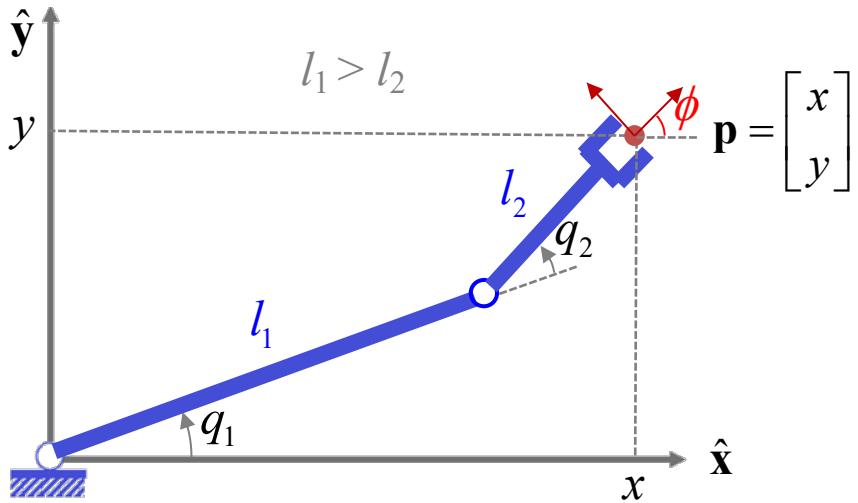
Workspace

- ABB's IRB 120 Robot



Workspace

Example: R-R Robot



- Workspace ($l_1 > l_2$):

$$WS = \{\mathbf{p} \in \mathbb{R}^2 : |l_1 - l_2| \leq \|\mathbf{p}\| \leq l_1 + l_2\}$$

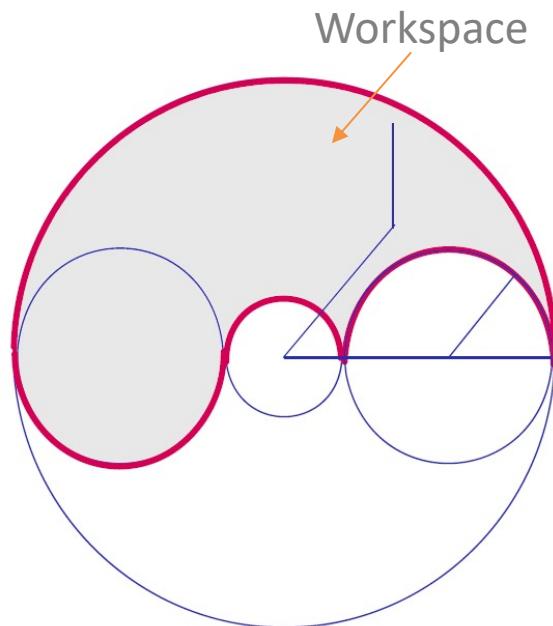
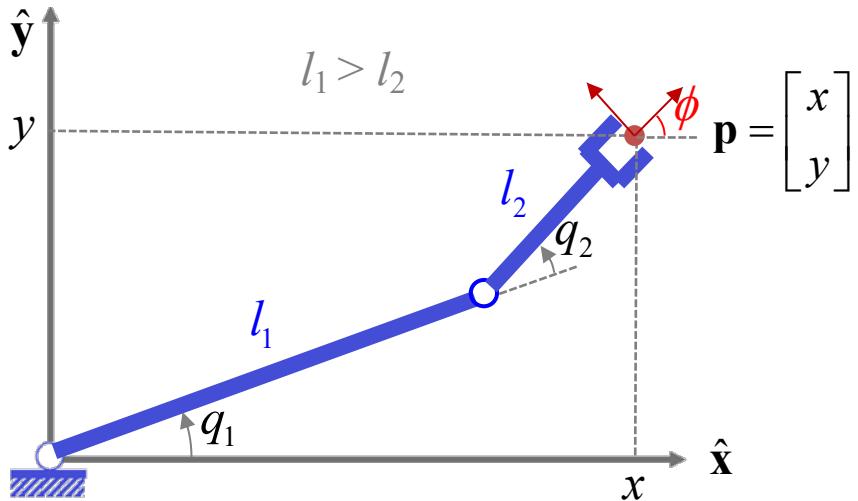
with $q_1 \in [0, 2\pi]$, $q_2 \in [0, 2\pi]$

Workspace: WS

Does the workspace change if joint limits are considered?

Workspace

Example: R-R Robot

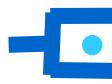


- If $q_1 \in [0, \pi]$, $q_2 \in [0, \pi]$, what is the workspace?
 - The workspace (WS) is reduced when joint limits are added
 - The analytic expression of the WS is more complicated

Workspace

- Primary Workspace (*reachable*): WS_1

Positions that can be reached with at least one orientation



Each point can be reached
(orientation “does not matter”)

- Out of WS_1 there is no solution to the problem
- For all $p \in WS_1$ (using a proper orientation), there is at least one solution

- Secondary Workspace (*dexterous*): WS_2

Positions can be reached with any orientation

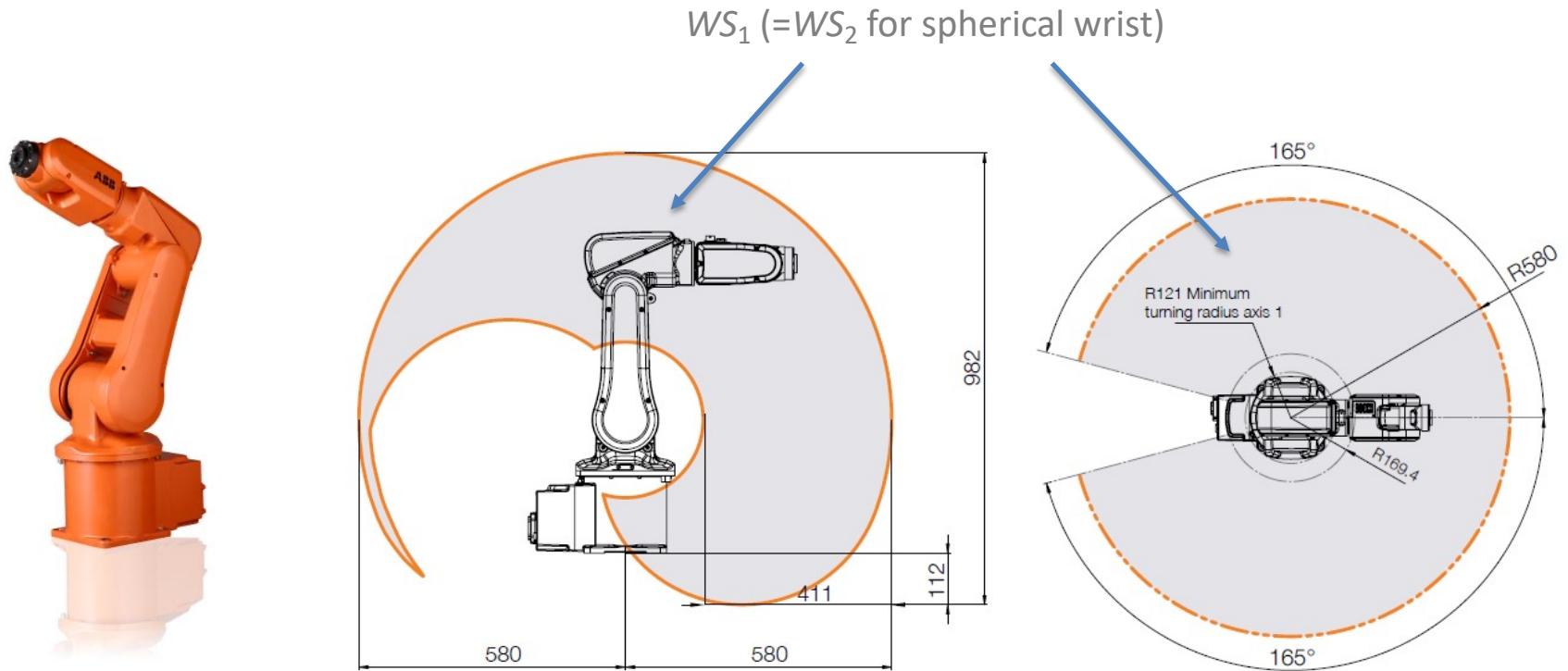


Reach every point with all
possible orientations

- For all $p \in WS_2$ there is (at least) one solution for every orientation
- Relation between WS_1 y WS_2 : $WS_2 \subseteq WS_1$

Workspace

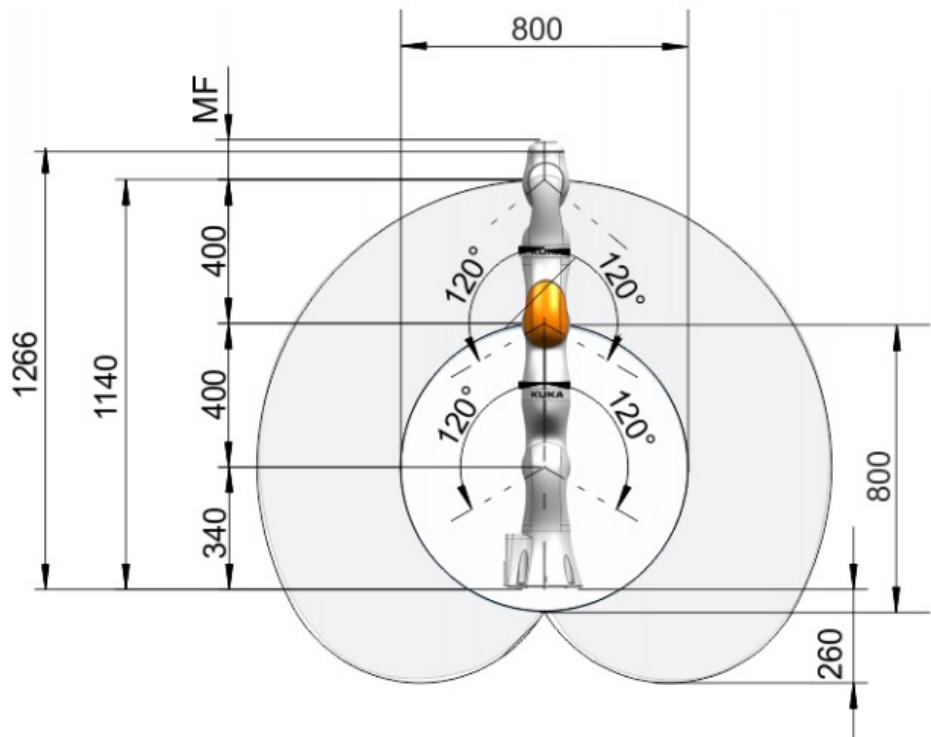
- Example: ABB's IRB 120 robot



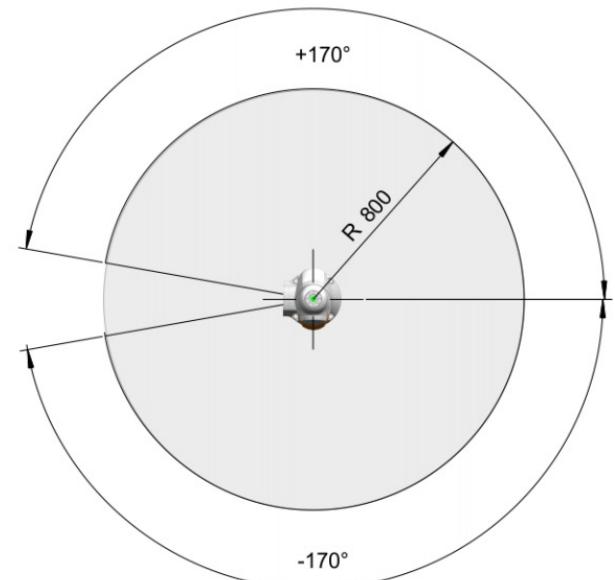
It is used to evaluate the robot for a specific application

Workspace

- Example: KUKA's LBR iiwa robot



Side View



Top View

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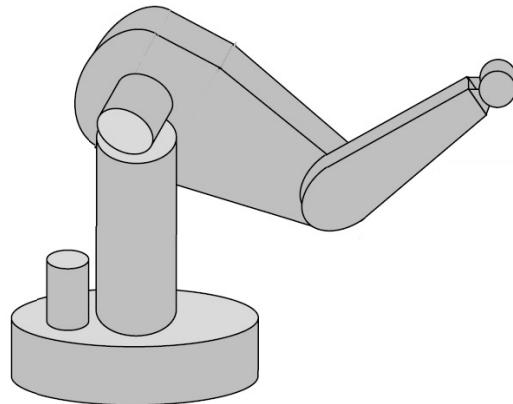
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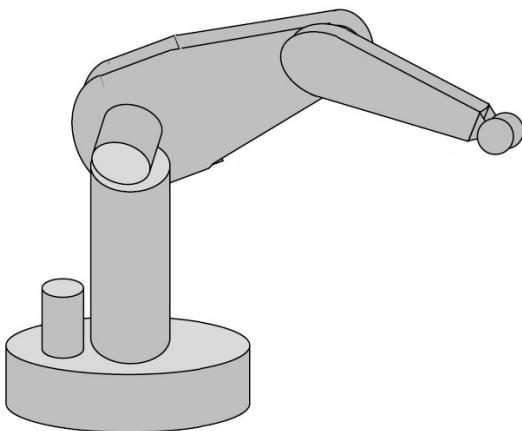
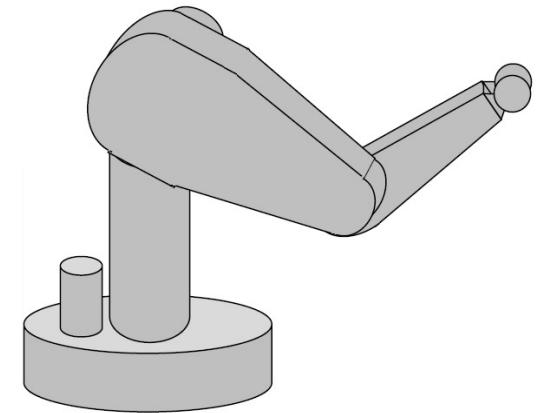
- Inverse Kinematics of Robot Manipulators -

Multiplicity of Solutions

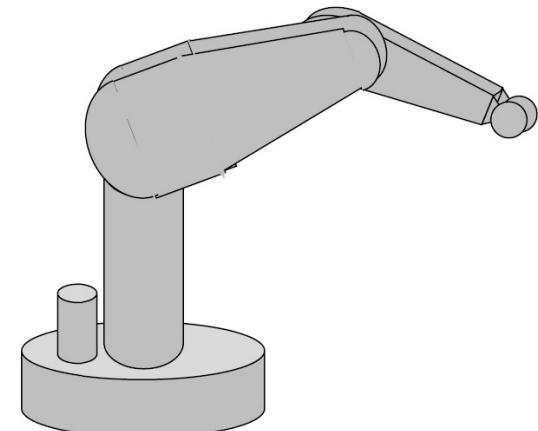
Example: PUMA Robot



If only position is considered,
the 4 configurations set the
end effector at the same point

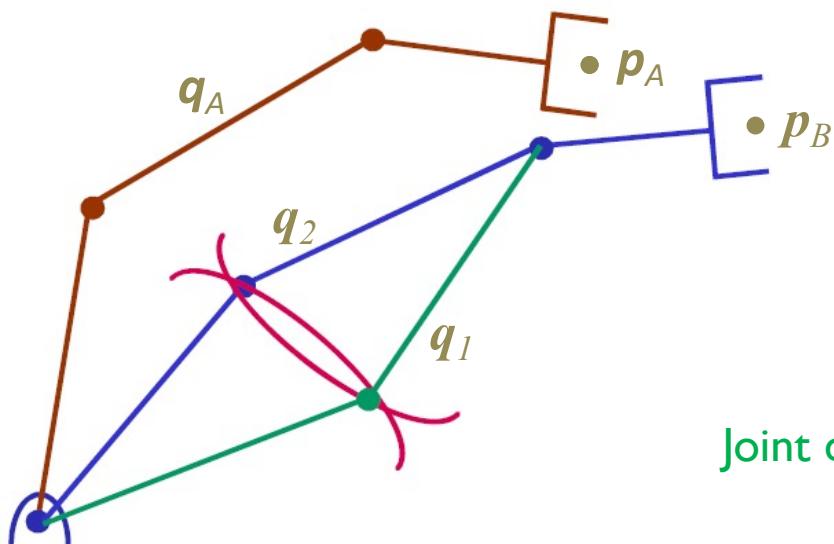


 Multiplicity of solutions



Multiplicity of Solutions

What solution to choose?



Initial configuration for p_A : q_A

New configurations for p_B : q_1, q_2

Is it better to choose q_1 or q_2 ? q_2

Joint distance between configurations:

$$\left. \begin{array}{l} d_1 \not\equiv \| \mathbf{q}_1 - \mathbf{q}_A \| \\ d_2 \not\equiv \| \mathbf{q}_2 - \mathbf{q}_A \| \end{array} \right\}$$

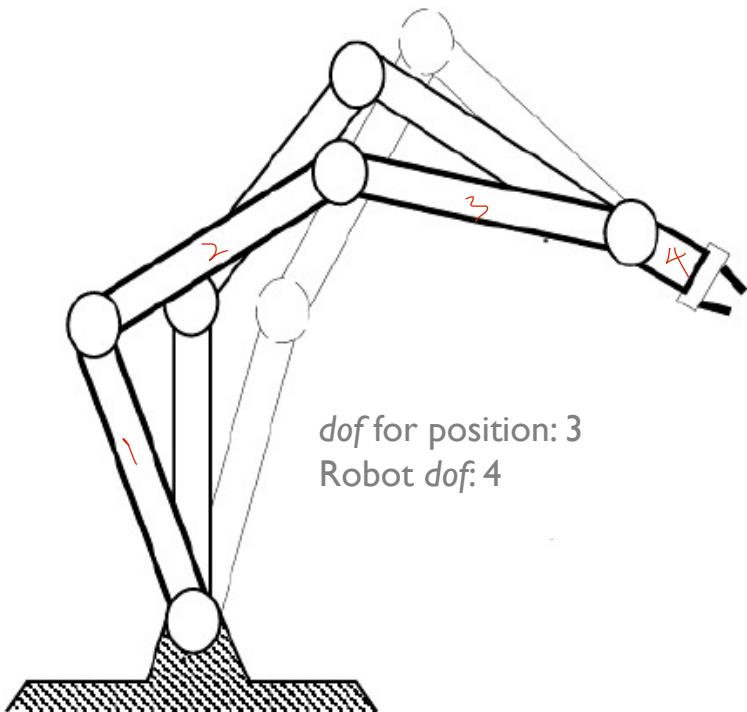
Shortest distance
is preferred

In general, if there are N possible configurations for \mathbf{p}_B , choose:

$$\mathbf{q}_b = \arg \min_{\mathbf{q}} \| \mathbf{q} - \mathbf{q}_A \| \quad \text{for} \quad \mathbf{q} \in \{\mathbf{q}_1, \mathbf{q}_2, \dots, \mathbf{q}_N\}$$

Multiplicity of Solutions

Redundancy



- **n joints:** $\mathbf{q} = (q_1, \dots, q_n)$

- **Task space:** $\mathbf{x} = (x_1, x_2, \dots, x_m)$

m : dimension of the task space

- Robot is redundant with respect to this task if: 多余的

$$n > m$$

- **Example:**

- A 6 dof robot is redundant if only position ($m = 3$) is considered (no orientation)
- A 6 dof robot is not redundant if position and orientation ($m = 6$) are considered

Inverse Kinematics

Complexity

- Equations are nonlinear
- There can be:
 - One solution
 - Multiple solutions
 - Infinite solutions (when there is **redundancy**)
 - No admissible solution (outside the workspace)
- When is the existence of a solution guaranteed for the position?
 - When the position (of the end effector) belongs to the reachable workspace
- When is the existence of a solution guaranteed for the pose?
 - When the pose (of the end effector) belongs to the **dexterous**

Inverse Kinematics

Solution Methods

- **Analytic Solution** (exact)
 - It is preferred, when it can be found
 - Methods:
 - Geometric ad-hoc approach
 - Algebraic approach (solution of polynomial equations)
 - Systematic reduction approach (obtain a reduced set of equations)
 - Kinematic decoupling (Pieper): robots with 6 dof
 - When the last 3 axes are revolute and they intersect each other (spherical wrist)
- **Numeric Solution** (iterative)
 - Needed when there is redundancy: $n > m$
 - Easier to obtain (slower run time?)
 - They use the **Jacobian matrix** of the forward kinematics
 -

Outline

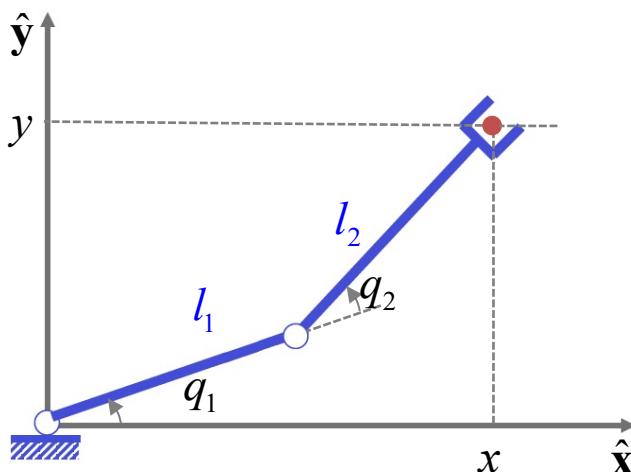
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- Inverse Kinematics of Robot Manipulators -

Geometric Solutions

- Applicable to robots with few *dofs* (3 or less)
- In robots with more dof, it can be applied to the first 3 dofs (if the other dofs are only used for orientation)
- It is not a generic solution → it depends on the robot
- Example:

Find the inverse kinematics for the position of the R-R robot using a geometric approach



Geometric Solutions

有时候三维问题可以转化为二维问题

- Example:

Find the inverse kinematics for the position of the R-R robot using a geometric approach

Solution

For q_2 :

- Using the law of cosines:

$$l^2 = l_1^2 + l_2^2 - 2l_1l_2 \cos(180 - q_2)$$

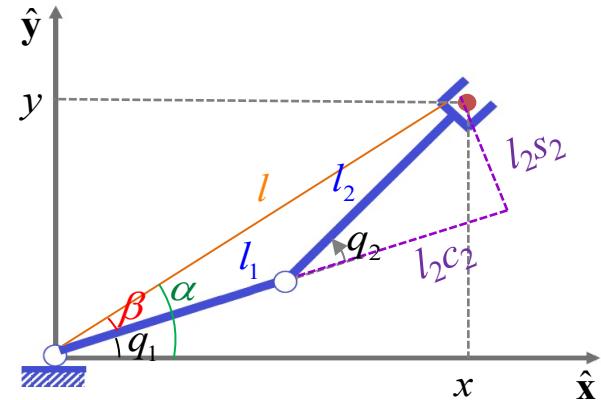
$$x^2 + y^2 = l_1^2 + l_2^2 + 2l_1l_2 \cos(q_2)$$

$$c_2 = \frac{x^2 + y^2 - (l_1^2 + l_2^2)}{2l_1l_2}$$

- Using a trigonometric identity:

$$\begin{aligned} s_2^2 + c_2^2 &= 1 \\ s_2 &= \pm\sqrt{1 - c_2^2} \end{aligned}$$

$$q_2 = \text{atan2}(s_2, c_2)$$



For q_1 (using the geometry of the figure)

$$q_1 = \alpha - \beta$$

$$\alpha = \text{atan2}(y, x)$$

$$\beta = \text{atan2}(l_2s_2, l_1 + l_2c_2)$$

Inverse kinematics:

$$q_1 = \text{atan2}(y, x) - \text{atan2}(l_2s_2, l_1 + l_2c_2)$$

$$q_2 = \text{atan2}(s_2, c_2)$$

Algebraic Solutions

- Solution using algebraic (and polynomial) equations
- Example:

Solution

- Forward kinematics:

$$x = l_1 c_1 + l_2 c_{12} \quad y = l_1 s_1 + l_2 s_{12}$$

- For q_2 :

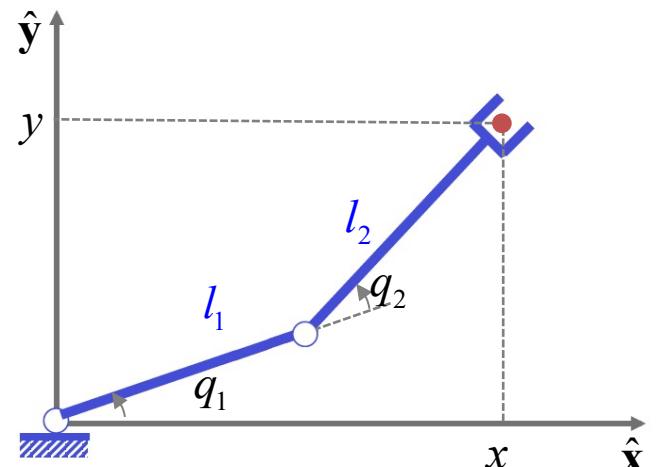
From F.K.

$$\begin{cases} x^2 = l_1^2 c_1^2 + l_2^2 c_{12}^2 + 2l_1 l_2 c_1 c_{12} \\ y^2 = l_1^2 s_1^2 + l_2^2 s_{12}^2 + 2l_1 l_2 s_1 s_{12} \end{cases}$$

$$x^2 + y^2 = l_1^2 + l_2^2 + 2l_1 l_2 (c_1 c_{12} + s_1 s_{12})$$

$$x^2 + y^2 = l_1^2 + l_2^2 + 2l_1 l_2 c_2$$

$$c_2 = \frac{x^2 + y^2 - (l_1^2 + l_2^2)}{2l_1 l_2}$$



$$s_2^2 + c_2^2 = 1$$

$$s_2 = \pm \sqrt{1 - c_2^2}$$

$$q_2 = \text{atan2}(s_2, c_2)$$

Algebraic Solutions

- Example:

Find the inverse kinematics for the position of the RR robot using an algebraic approach

Solution

- For q_1 (expanding terms from forward kinematics):

$$x = l_1 c_1 + l_2 (c_1 c_2 - s_1 s_2)$$

$$y = l_1 s_1 + l_2 (s_1 c_2 + c_1 s_2)$$

Equations are linear in c_1, s_1 : solve for them:

$$x = c_1(l_1 + l_2 c_2) - s_1(l_2 s_2)$$

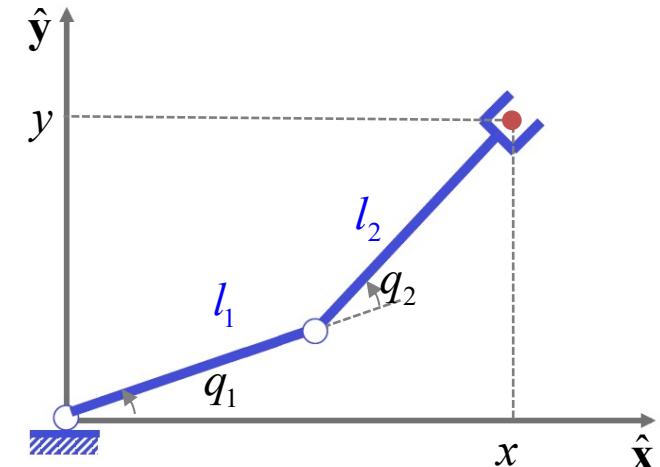
$$y = s_1(l_1 + l_2 c_1) + c_1(l_2 s_2)$$

In matrix form:

$$\begin{bmatrix} l_1 + l_2 c_2 & -l_2 s_2 \\ l_2 s_2 & l_1 + l_2 c_2 \end{bmatrix} \begin{bmatrix} c_1 \\ s_1 \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix}$$

solving 

$$q_1 = \text{atan2}(s_1, c_1)$$



$$\left\{ \begin{array}{l} s_1 = \frac{y(l_1 + l_2 c_2) - xl_2 s_2}{\det} \\ c_1 = \frac{x(l_1 + l_2 c_2) + yl_2 s_2}{\det} \\ \det = l_1^2 + l_2^2 + 2l_1 l_2 c_2 \end{array} \right.$$

Algebraic Solutions

- Example 2

For a 3-dof robot, its end effector pose with respect to its base is given by

$${}^0T_3 = \begin{bmatrix} \cos(\theta_1 + \theta_3) & 0 & \sin(\theta_1 + \theta_3) & a_3 \cos(\theta_1 + \theta_3) + q_2 \sin \theta_1 \\ \sin(\theta_1 + \theta_3) & 0 & -\cos(\theta_1 + \theta_3) & a_3 \sin(\theta_1 + \theta_3) - q_2 \cos(\theta_1) \\ 0 & 1 & 0 & d_1 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

where a_3 and d_1 are constants. The desired pose for the end effector is:

$$T_{des} = \begin{bmatrix} n_x & o_x & a_x & p_x \\ n_y & o_y & a_y & p_y \\ n_z & o_z & a_z & p_z \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Find the inverse kinematics () of this robot as a function of the elements of T_{des} .

Solution

The procedure consists in obtaining relations between both matrices, and applying some algebra, so that the value for each joint can be solved.

Algebraic Solutions

- Example 2

- Finding :

$$\left\{ \begin{array}{l} p_x = a_3 c_{13} + s_1 q_2 \longrightarrow p_x - a_3 c_{13} = s_1 q_2 \\ p_y = a_3 s_{13} - c_1 q_2 \longrightarrow a_3 s_{13} - p_y = c_1 q_2 \end{array} \right.$$

$$\tan(\theta_1) = \frac{p_x - a_3 c_{13}}{a_3 s_{13} - p_y} = \frac{p_x - a_3 n_x}{a_3 n_y - p_y} \quad \Rightarrow \quad \theta_1 = \text{atan2}(p_x - a_3 n_x, a_3 n_y - p_y)$$

- Finding θ_3 :

$$\frac{a_x}{n_x} = \tan(\theta_1 + \theta_3) \longrightarrow \theta_1 + \theta_3 = \text{atan2}(a_x, n_x)$$

$$\theta_3 = \text{atan2}(a_x, n_x) - \theta_1$$

- Finding θ_2 :

$$\left\{ \begin{array}{l} s_1 p_x = a_3 s_1 c_{13} + s_1^2 q_2 \\ c_1 p_y = a_3 s_{13} c_1 - c_1^2 q_2 \end{array} \right.$$

$$s_1 p_x - c_1 p_y = a_3(s_1 n_x - n_y c_1) + q_2$$

$$q_2 = s_1 p_x - c_1 p_y - a_3(s_1 n_x - n_y c_1)$$

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4. Analytic solutions
- 5. Numeric solutions**
6. Numeric computation of the Jacobian

- Inverse Kinematics of Robot Manipulators -

Numeric Solutions

- They are mainly used when:

- There is no analytic solution
- There are infinite solutions (e.g. redundant robots)
- It is “too complicated” to find a solution

- Idea:

$$\underbrace{\mathbf{x} = f(\mathbf{q})}_{\text{Forward kinematics}}$$

Find \mathbf{q} (using iterations) such that
the difference is zero

$$J(\mathbf{q}) = \frac{\partial f(\mathbf{q})}{\partial \mathbf{q}}$$

$$f(q_s + \xi) = f(q_s) + \frac{f'(q_s)}{1!} \xi + \frac{f''(q_s)}{2!} \xi^2$$

$$f(q_s + \xi) - f(q_s) = f'(q_s) \xi$$

$$\Delta \mathbf{x} \approx f'(\mathbf{q}_s) \Delta \mathbf{q}$$

$$f'(q_s) = \frac{\partial f(q_s)}{\partial q_s}$$

- They use the Jacobian matrix:

- Usual solution methods:
 - Newton's method
 - Gradient descent method

Notes:

- In robotics, the Jacobian matrix is known as the analytic Jacobian
 - n : size of \mathbf{q} (number of joints)
 - m : size of \mathbf{x} (size of the task space)

$$\vec{f}(q) = \begin{pmatrix} f_x(q) \\ f_y(q) \end{pmatrix}$$

$$\vec{f}(\vec{q} + \vec{\varepsilon}) = \vec{f}(\vec{q}) + \begin{pmatrix} \frac{\partial f_x}{\partial q_1} & \frac{\partial f_x}{\partial q_2} \\ \frac{\partial f_y}{\partial q_1} & \frac{\partial f_y}{\partial q_2} \end{pmatrix} \vec{\varepsilon} \quad \vec{\varepsilon} = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix}$$

Jacob Matrix

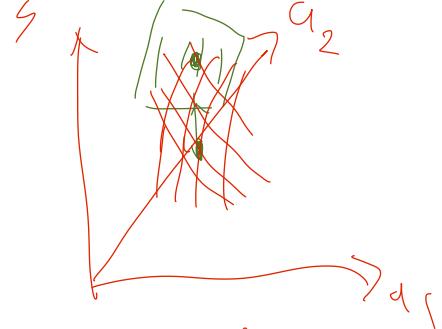
$$\vec{J} = \begin{pmatrix} \frac{\partial f_1}{\partial q_1} & \cdots & \frac{\partial f_1}{\partial q_n} \\ \vdots & & \vdots \\ \frac{\partial f_n}{\partial q_1} & \cdots & \frac{\partial f_n}{\partial q_n} \end{pmatrix}$$

$$\frac{d\vec{x}}{dt} = \vec{J} \cdot \frac{d\vec{\theta}}{dt}$$

can be changed to

$$\dot{\vec{x}} = \vec{J} \vec{\dot{\theta}}$$

only for no redundant problem



$$s = f_1 \left(\begin{pmatrix} q_1 \\ q_2 \end{pmatrix} \right)$$

$$v_1 = \frac{\partial f}{\partial q_1}$$

$$v_2 = \frac{\partial f}{\partial q_2}$$

Numeric Solutions

a) Newton's Method

- **Problem:** given a (constant) x_d , find q such that

$$\mathbf{x}_d - f(\mathbf{q}) = 0$$

x_d : desired value for x
 f : forward kinematics function

- **Procedure for the solution**

- First order Taylor approximation for $f(\mathbf{q})$

$$f(\mathbf{q}) \approx f(\mathbf{q}_k) + J(\mathbf{q}_k)(\mathbf{q} - \mathbf{q}_k)$$

$$J(\mathbf{q}_k) = \frac{\partial f(\mathbf{q}_k)}{\partial \mathbf{q}}$$

←
Jacobian matrix

- Replacing:

$$\mathbf{x}_d - (f(\mathbf{q}_k) + J(\mathbf{q}_k)(\mathbf{q} - \mathbf{q}_k)) = 0$$

- Assuming J is square and invertible ($n = m$):

$$\mathbf{x}_d - f(\mathbf{q}_k) = J(\mathbf{q}_k)(\mathbf{q} - \mathbf{q}_k)$$

- **Final solution ($\mathbf{q} = \mathbf{q}_{k+1}$):**

Newton Method find J^{-1}

$$J^{-1}(\mathbf{q}_k) (\mathbf{x}_d - f(\mathbf{q}_k)) = (\mathbf{q} - \mathbf{q}_k)$$

$$\mathbf{q}_{k+1} = \mathbf{q}_k + J^{-1}(\mathbf{q}_k) (\mathbf{x}_d - f(\mathbf{q}_k))$$

Numeric Solutions

a) Newton's Method

- **Algorithm:**

- Start with an initial \mathbf{q}_0 (usually the current configuration)
- Iteratively update using:

$$\mathbf{q}_{k+1} = \mathbf{q}_k + J^{-1}(\mathbf{q}_k)(\mathbf{x}_d - f(\mathbf{q}_k)) \quad k = 0, 1, 2, 3, \dots$$

- Stop when:

$$\underbrace{\|\mathbf{x}_d - f(\mathbf{q}_k)\| < \varepsilon}_{\text{Small Cartesian error}} \quad \text{or} \quad \underbrace{\|\mathbf{q}_{k+1} - \mathbf{q}_k\| < \varepsilon}_{\text{Small joint increment}}$$

ε : small value

- **Comments:**

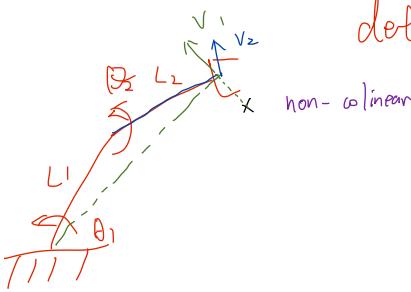
- Convergence if we start with \mathbf{q}_0 (initial value) close to the solution
- When there is redundancy ($m < n$):

J is not square (and there is no inverse)! → we use the pseudo-inverse

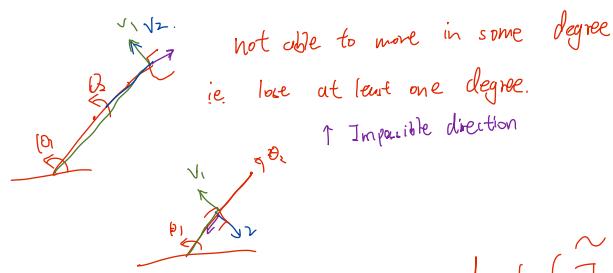
- **Disadvantages:**

- Computation time of the inverse (or pseudo-inverse)
- Problems near singularities of J (Jacobian matrix)

- **Advantage:** it is fast (quadratic convergence)



$$\det(\tilde{J}) = 0 \rightarrow \theta_2 = \{0^\circ, 180^\circ\}$$



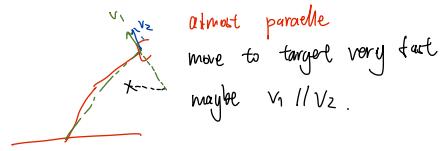
$$\tilde{A}^T | \tilde{y} = \tilde{A} b'$$

$$(\tilde{A}^T A)^{-1} | \tilde{A}^T \tilde{y} = \tilde{A}^T \tilde{A} b.$$

$$\underline{(\tilde{A}^T A)^{-1} \tilde{A}^T \tilde{y}} = b.$$

\tilde{J}

$\det(\tilde{J}) = 0 \leftarrow$ singular cond
Inversible



$$\lim_{\Delta t \rightarrow 0} \frac{\Delta \vec{x}}{\Delta t} = \tilde{J} \cdot \frac{\partial \vec{x}}{\partial t}$$

$$\Rightarrow \dot{\vec{x}} = \tilde{J} \cdot \dot{\vec{\theta}}$$

$$\vec{x} = \begin{pmatrix} x \\ y \\ z \\ K\vec{\theta} \\ K\vec{\dot{\theta}} \end{pmatrix}$$

$$\begin{matrix} \dot{\vec{x}} \\ \dot{\vec{\theta}} \end{matrix} \quad \left| \quad \begin{matrix} \dot{\vec{x}} \\ \dot{\vec{\theta}} \end{matrix} = \begin{pmatrix} \tilde{J}_v \\ \tilde{J}_w \end{pmatrix} \cdot \dot{\vec{\theta}} \right.$$

↓

$$\begin{matrix} \dot{\vec{x}} \\ \dot{\vec{\theta}} \end{matrix} = \begin{pmatrix} iR & iT \\ 0 & 1 \end{pmatrix} \cdot \begin{pmatrix} p_x \\ p_y \\ p_z \\ 0 \end{pmatrix} \quad \begin{matrix} \dot{\vec{P}} = iR \cdot \dot{\vec{P}} + iT \end{matrix}$$

$$\begin{matrix} \dot{\vec{v}} \\ \dot{\vec{\theta}} \end{matrix} = \begin{pmatrix} v_x \\ v_y \\ v_z \\ 0 \end{pmatrix} \quad \begin{matrix} \dot{\vec{V}} = iR \cdot \dot{\vec{V}} \end{matrix}$$

$$\dot{\vec{x}} = (\) \dot{\vec{x}}$$

$$\begin{pmatrix} \dot{\vec{x}} \\ \dot{\vec{\theta}} \end{pmatrix} = \begin{pmatrix} i\tilde{R} & i\tilde{O} \\ 0 & i\tilde{R} \end{pmatrix} \cdot \begin{pmatrix} \dot{\vec{x}} \\ \dot{\vec{\theta}} \end{pmatrix}$$

$$j \begin{pmatrix} \dot{\vec{x}}_p \\ \dot{\vec{x}}_w \end{pmatrix} = \begin{pmatrix} j\hat{R} & 0 \\ 0 & j\hat{\mathcal{L}} \end{pmatrix} i \begin{pmatrix} \hat{\vec{J}}_v \\ \hat{\vec{J}}_w \end{pmatrix} \cdot \dot{\vec{\theta}}$$

↓.

$$j \hat{\vec{f}} = j \begin{pmatrix} \hat{\vec{J}}_v \\ \hat{\vec{J}}_w \end{pmatrix} = \begin{pmatrix} j\hat{R} & 0 \\ 0 & j\hat{\mathcal{L}} \end{pmatrix} i \hat{\vec{J}}$$

Numeric Solutions

a) Newton's Method

- **Example:** RR robot

Compute the joint values needed for the end effector to be at $x = 1.2, y = 1.2$ using Newton's method. Assume that $l_1 = l_2 = 1$

Solution

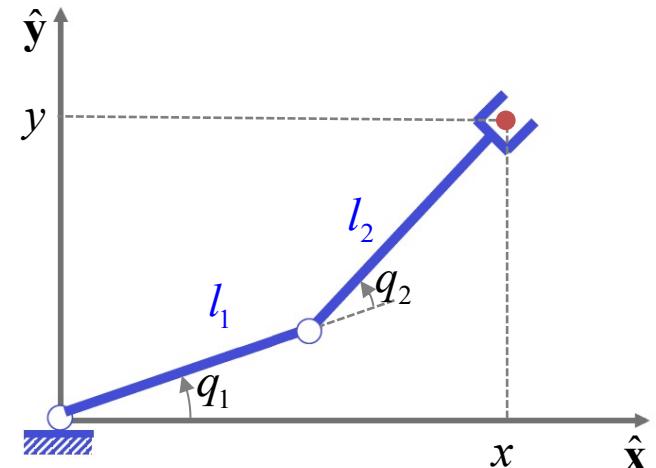
- Forward kinematics: $f(\mathbf{q}) = \begin{bmatrix} c_1 + c_{12} \\ s_1 + s_{12} \end{bmatrix}$

- Jacobian matrix:

$$J(\mathbf{q}) = \frac{\partial f(\mathbf{q})}{\partial \mathbf{q}} = \begin{bmatrix} \frac{\partial f_x}{\partial q_1} & \frac{\partial f_x}{\partial q_2} \\ \frac{\partial f_y}{\partial q_1} & \frac{\partial f_y}{\partial q_2} \end{bmatrix} = \begin{bmatrix} -(s_1 + s_{12}) & -s_{12} \\ c_1 + c_{12} & c_{12} \end{bmatrix}$$

- Inverse of the Jacobian:

$$J^{-1}(\mathbf{q}) = \frac{1}{s_2} \begin{bmatrix} c_{12} & s_{12} \\ -(c_1 + c_{12}) & -(s_1 + s_{12}) \end{bmatrix}$$



Desired position:

$$\mathbf{x}_d = \begin{bmatrix} 1.2 \\ 1.2 \end{bmatrix}$$

Numeric Solutions

a) Newton's Method

- **Example:** RR robot

Compute the joint values needed for the end effector to be at $x = 1.2, y = 1.2$ using Newton's method. Assume that $l_1 = l_2 = 1$.

Solution

- Expression for Newton's method:

$$\mathbf{q}_{k+1} = \mathbf{q}_k + J^{-1}(\mathbf{q}_k)(\mathbf{x}_d - f(\mathbf{q}))$$

- Replacing the previous values:

$$\mathbf{q}_{k+1} = q_k + \left(\begin{matrix} \frac{1}{s_2} & c_{12} \\ -(c_1 + c_{12}) & -(s_1 + s_{12}) \end{matrix} \right) \underbrace{\left(\begin{bmatrix} 1.2 \\ 1.2 \end{bmatrix} - \begin{bmatrix} c_1 + c_{12} \\ s_1 + s_{12} \end{bmatrix} \right)}_{\text{Current error}}$$

- It is iteratively applied

For example, use $q_1 = 0.5$ y $q_2 = 0.5$ as initial values (note: we cannot start with $q_2 = 0$ since J^{-1} would not exist)

Numeric Solutions

a) Newton's Method

- Example: RR robot

```
import numpy as np
cos=np.cos; sin=np.sin

xd = np.array([1.2, 1.2]) # Desired value in the Cartesian space
q  = np.array([0.5, 0.5]) # Initial value in the joint space
epsilon = 1e-3
max_iter = 100 # Maximum number of iterations

# Iterations: Newton's method
for i in range(max_iter):
    q1 = q[0]; q2 = q[1];
    J = np.array([
        [-sin(q1)-sin(q1+q2), -sin(q1+q2)],
        [cos(q1)+cos(q1+q2), cos(q1+q2)]])
    f = np.array([cos(q1)+cos(q1+q2), sin(q1)+sin(q1+q2)])
    e = xd-f
    q = q + np.dot(np.linalg.inv(J), e)
    # End condition
    if (np.linalg.norm(e) < epsilon):
        break
print(q)
```

Numeric Solutions

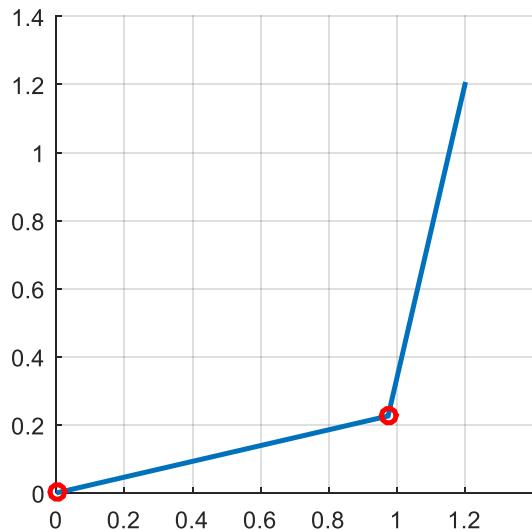
a) Newton's Method

- **Example:** RR robot

- Note that the result depends on the initial value.

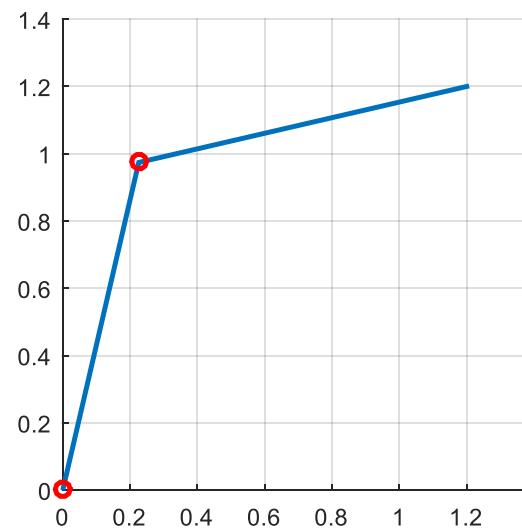
-

$$\mathbf{q} = \begin{bmatrix} 0.2278 \\ 1.1157 \end{bmatrix}$$



Final configuration when the initial value was $\mathbf{q} = [0.5; 0.5]$

$$\mathbf{q} = \begin{bmatrix} 1.3430 \\ -1.1152 \end{bmatrix}$$



Final configuration when the initial value was $\mathbf{q} = [1; -1]$

(Generic Gradient Descent)

- **Objective:**

- Minimize the generic function $g(\mathbf{q})$

$$\min_{\mathbf{q}} g(\mathbf{q})$$

- **Idea:**

- Start with an initial value \mathbf{q}_0
- “Move” in the negative direction of the gradient (g), iteratively

$$\mathbf{q}_{k+1} = \mathbf{q}_k - \alpha \nabla g(\mathbf{q}_k) \quad \alpha \in \sim^+ : \text{size of the step}$$

- The step size $\alpha > 0$ must guarantee a maximum descent of $g(\mathbf{q})$ in every iteration:
 - α very high: it can lead to divergence (the minimum is not found)
 - α very small: it generates a slow convergence

Recall that the gradient indicates the direction of maximum variation

Numeric Solutions

b) Gradient Descent Method

- Forward kinematics: $\mathbf{x}_d = f(\mathbf{q})$ or equivalently

$$\underbrace{\mathbf{x}_d - f(\mathbf{q})}_{\text{error}} = 0$$

• Procedure:

- Define a scalar **error** function:

$$g(\mathbf{q}) = \frac{1}{2} \| \mathbf{x}_d - f(\mathbf{q}) \|^2 \quad \leftarrow \quad g : \mathbb{R}^n \rightarrow \mathbb{R}$$

- **Objective:** minimize the error:

$$\min_{\mathbf{q}} g(\mathbf{q})$$

- Compute the gradient of $g(\mathbf{q})$:

$$g(\mathbf{q}) = \frac{1}{2} (\mathbf{x}_d - f(\mathbf{q}))^T (\mathbf{x}_d - f(\mathbf{q})) \quad \rightarrow \quad \nabla g(\mathbf{q}) = - \underbrace{\left(\frac{\partial f(\mathbf{q})}{\partial \mathbf{q}} \right)^T}_{J(\mathbf{q})} (\mathbf{x}_d - f(\mathbf{q}))$$

- Apply gradient descent

$$\mathbf{q}_{k+1} = \mathbf{q}_k - \alpha \nabla g(\mathbf{q}_k)$$

$$\mathbf{q}_{k+1} = \mathbf{q}_k + \alpha J^T(\mathbf{q}_k) (\mathbf{x}_d - f(\mathbf{q}_k))$$

- **Pros:** computationally simpler (transpose instead of inverse)
- **Cons:**

Numeric Solutions

b) Gradient Descent Method

- **Example:** RR robot

Compute the joint values for the end effector to be at $x = 1.2, y = 1.2$ using the gradient descent method. Assume that $l_1 = l_2 = 1$

Solution

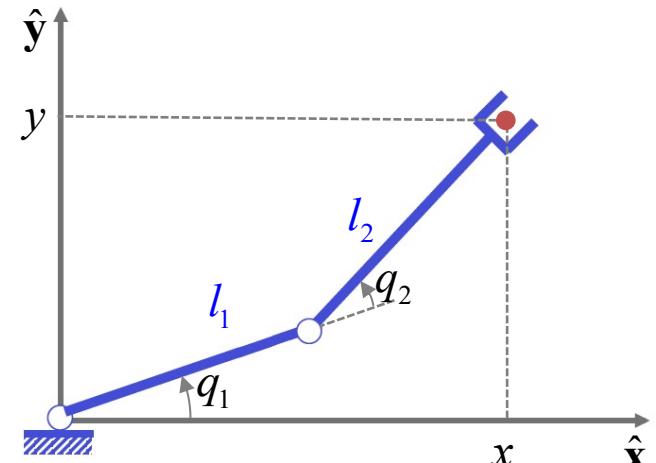
- Forward kinematics $f(\mathbf{q}) = \begin{bmatrix} c_1 + c_{12} \\ s_1 + s_{12} \end{bmatrix}$

- Jacobian matrix:

$$J(\mathbf{q}) = \frac{\partial f(\mathbf{q})}{\partial \mathbf{q}} = \begin{bmatrix} \frac{\partial f_x}{\partial q_1} & \frac{\partial f_x}{\partial q_2} \\ \frac{\partial f_y}{\partial q_1} & \frac{\partial f_y}{\partial q_2} \end{bmatrix} = \begin{bmatrix} -(s_1 + s_{12}) & -s_{12} \\ c_1 + c_{12} & c_{12} \end{bmatrix}$$

- Transpose of the Jacobian:

$$J^T(\mathbf{q}) = \begin{bmatrix} -(s_1 + s_{12}) & c_1 + c_{12} \\ -s_{12} & c_{12} \end{bmatrix}$$



Desired position:

$$\mathbf{x}_d = \begin{bmatrix} 1.2 \\ 1.2 \end{bmatrix}$$

Numeric Solutions

b) Gradient Descent Method

- **Example:** RR robot

Compute the joint values for the end effector to be at $x = 1.2, y = 1.2$ using the gradient descent method. Assume that $l_1 = l_2 = 1$.

Solution

- Expression for gradient descent:

$$\mathbf{q}_{k+1} = \mathbf{q}_k + \alpha J^T(\mathbf{q}_k)(\mathbf{x}_d - f(\mathbf{q}))$$

- Replacing the previous values:

$$\mathbf{q}_{k+1} = q_k + \alpha \begin{bmatrix} -(s_1 + s_{12}) & (c_1 + c_{12}) \\ -s_{12} & c_{12} \end{bmatrix} \left(\begin{bmatrix} 1.2 \\ 1.2 \end{bmatrix} - \underbrace{\begin{bmatrix} c_1 + c_{12} \\ s_1 + s_{12} \end{bmatrix}}_{\text{Current error}} \right)$$

- It is iteratively applied.

For example, use $q_1 = 0.5$ y $q_2 = 0.5$ as initial values (in this case we can start with $q_2 = 0$)

Numeric Solutions

b) Gradient Descent Method

- Example: RR robot

```
import numpy as np
cos=np.cos; sin=np.sin

xd = np.array([1.2, 1.2]) # Desired value in the Cartesian space
q = np.array([0.5, 0.5]) # Initial value in the joint space
epsilon = 1e-3
max_iter = 1000      # Maximum number of iterations
alpha = 0.5

# Iterations: Gradient descent
for i in range(max_iter):
    q1 = q[0]; q2 = q[1];
    J = np.array([[ -sin(q1)-sin(q1+q2), -sin(q1+q2)],
                  [ cos(q1)+cos(q1+q2),  cos(q1+q2)]])
    f = np.array([cos(q1)+cos(q1+q2), sin(q1)+sin(q1+q2)])
    e = xd-f
    q = q + alpha*np.dot(J.T, e)
    # End condition
    if (np.linalg.norm(e) < epsilon):
        break
print(q)
```

Numeric Solutions

Comparison

- **Newton's method**
 - Quadratic convergence rate (it is fast)
 - Problems near singularities (singularities can be computed using the singular values of J)
- **Gradient descent method**
 - Linear convergence rate (it is slow)
 - It does not have singularity problems
 - The step size (α) must be carefully chosen (but there exist adaptive methods such as line search)
- **Efficient algorithm:**
 - Start with the gradient descent method (safe, but slow)
 -

Outline

1. Introduction
2. Workspace (and existence of solutions)
3. Multiplicity of solutions
4. Analytic solutions
5. Numeric solutions
6. **Numeric Computation of the Jacobian**

- Inverse Kinematics of Robot Manipulators -

Numeric Computation of the Jacobian

- For complex robots:
 - Very tedious to manually compute the Jacobian
- Alternative:
 - Compute the Jacobian numerically: numeric differentiation
- The Jacobian (considering only position) of an n dof robot is:

Each column is the variation with respect to a given angle:

$$J(\mathbf{q}) = \begin{bmatrix} \frac{\partial x}{\partial q_1} & \frac{\partial x}{\partial q_2} & \cdots & \frac{\partial x}{\partial q_n} \\ \frac{\partial y}{\partial q_1} & \frac{\partial y}{\partial q_2} & \cdots & \frac{\partial y}{\partial q_n} \\ \frac{\partial z}{\partial q_1} & \frac{\partial z}{\partial q_2} & \cdots & \frac{\partial z}{\partial q_n} \end{bmatrix}$$

position

$$J(\mathbf{q}) = \begin{bmatrix} \frac{\partial \mathbf{x}_p}{\partial q_1} & \frac{\partial \mathbf{x}_p}{\partial q_2} & \cdots & \frac{\partial \mathbf{x}_p}{\partial q_n} \end{bmatrix}$$

$\mathbf{x}_p = (x, y, z)$
 $\mathbf{x}_p = \mathbf{f}(q_1, \dots, q_n)$

- Approximation of the derivative of the position x_p with respect to joint q_i

$$\frac{\partial \mathbf{x}_p}{\partial q_i} \approx \frac{\Delta \mathbf{x}_p}{\Delta q_i} = \frac{\mathbf{f}(q_1, \dots, q_i + \Delta q_i, \dots, q_n) - \mathbf{f}(q_1, \dots, q_n)}{\Delta q_i}$$

Increment only for joint q_i

Numeric Computation of the Jacobian

- Example

Consider the following forward kinematics (R-R Robot with $l_1 = l_2 = 1$):

$$f(\mathbf{q}) = \begin{bmatrix} f_x(\mathbf{q}) \\ f_y(\mathbf{q}) \end{bmatrix} = \begin{bmatrix} \cos(q_1) + \cos(q_1 + q_2) \\ \sin(q_1) + \sin(q_1 + q_2) \end{bmatrix}$$

Compute the Jacobian numerically when the joint values are $q_1 = 0.5, q_2$

Solution

- The Jacobian is:

$$J(\mathbf{q}) = \begin{bmatrix} \frac{\partial f_x}{\partial q_1} & \frac{\partial f_x}{\partial q_2} \\ \frac{\partial f_y}{\partial q_1} & \frac{\partial f_y}{\partial q_2} \end{bmatrix}$$

- Derivatives with respect to q_1 (first column):

$$\frac{\partial f_x}{\partial q_1} = \frac{f_x(q_1 + \Delta q_1, q_2) - f_x(q_1, q_2)}{\Delta q_1} = \frac{[\cos(q_1 + \Delta q_1) + \cos((q_1 + \Delta q_1) + q_2)] - (\cos(q_1) + \cos(q_1 + q_2))}{\Delta q_1}$$

$$\frac{\partial f_y}{\partial q_1} = \frac{f_y(q_1 + \Delta q_1, q_2) - f_y(q_1, q_2)}{\Delta q_1} = \frac{[\sin(q_1 + \Delta q_1) + \sin((q_1 + \Delta q_1) + q_2)] - (\sin(q_1) + \sin(q_1 + q_2))}{\Delta q_1}$$

Numeric Computation of the Jacobian

- Example

Consider the following forward kinematics (R-R Robot with $l_1 = l_2 = 1$):

$$f(\mathbf{q}) = \begin{bmatrix} f_x(\mathbf{q}) \\ f_y(\mathbf{q}) \end{bmatrix} = \begin{bmatrix} \cos(q_1) + \cos(q_1 + q_2) \\ \sin(q_1) + \sin(q_1 + q_2) \end{bmatrix}$$

Compute the Jacobian numerically when the joint values are $q_1 = 0.5, q_2 = 1.0$

Solution

- The Jacobian is:

$$J(\mathbf{q}) = \begin{bmatrix} \frac{\partial f_x}{\partial q_1} & \frac{\partial f_x}{\partial q_2} \\ \frac{\partial f_y}{\partial q_1} & \frac{\partial f_y}{\partial q_2} \end{bmatrix}$$

- Derivatives with respect to q_2 (second column):

$$\frac{\partial f_x}{\partial q_2} = \frac{f_x(q_1, q_2 + \Delta q_2) - f_x(q_1, q_2)}{\Delta q_2} = \frac{[\cos(q_1) + \cos(q_1 + (q_2 + \Delta q_2))] - (\cos(q_1) + \cos(q_1 + q_2))}{\Delta q_2}$$

$$\frac{\partial f_y}{\partial q_2} = \frac{f_y(q_1, q_2 + \Delta q_2) - f_y(q_1, q_2)}{\Delta q_2} = \frac{[\sin(q_1) + \sin(q_1 + (q_2 + \Delta q_2))] - (\sin(q_1) + \sin(q_1 + q_2))}{\Delta q_2}$$

Numeric Computation of the Jacobian

- Example

- Using $\Delta q_1 = \Delta q_2 = 0.001$:

$$\frac{\partial f_x}{\partial q_1} = \frac{(\cos(0.5 + 0.001) + \cos(0.5 + 0.001 + 1.0)) - (\cos(0.5) + \cos(0.5 + 1.0))}{0.001} = -1.4774$$

$$\frac{\partial f_y}{\partial q_1} = \frac{(\sin(0.5 + 0.001) + \sin(0.5 + 0.001 + 1.0)) - (\sin(0.5) + \sin(0.5 + 1.0))}{0.001} = 0.9476$$

$$\frac{\partial f_x}{\partial q_2} = \frac{(\cos(0.5) + \cos(0.5 + 1.0 + 0.001)) - (\cos(0.5) + \cos(0.5 + 1.0))}{0.001} = -0.9975$$

$$\frac{\partial f_y}{\partial q_2} = \frac{(\sin(0.5) + \sin(0.5 + 1.0 + 0.001)) - (\sin(0.5) + \sin(0.5 + 1.0))}{0.001} = 0.0702$$

- Jacobian using the numeric computation:

$$J(\mathbf{q}) = \begin{bmatrix} -1.4774 & -0.9975 \\ 0.9476 & 0.0702 \end{bmatrix}$$

Jacobian using the analytical approach
(for comparison)

$$J(\mathbf{q}) = \begin{bmatrix} -1.4769 & -0.9975 \\ 0.9483 & 0.0707 \end{bmatrix}$$

Similar values (within rounding errors)

Numeric Computation of the Jacobian

- Example

Computationally (using Python):

- Forward kinematics function

```
def fkine(q):
    x = np.cos(q[0]) + np.cos(q[0]+q[1]);
    y = np.sin(q[0]) + np.sin(q[0]+q[1]);
    return np.array([x,y])
```

- Computation of the Jacobian

```
q1 = 0.5; q2 = 1.0
delta = 0.001

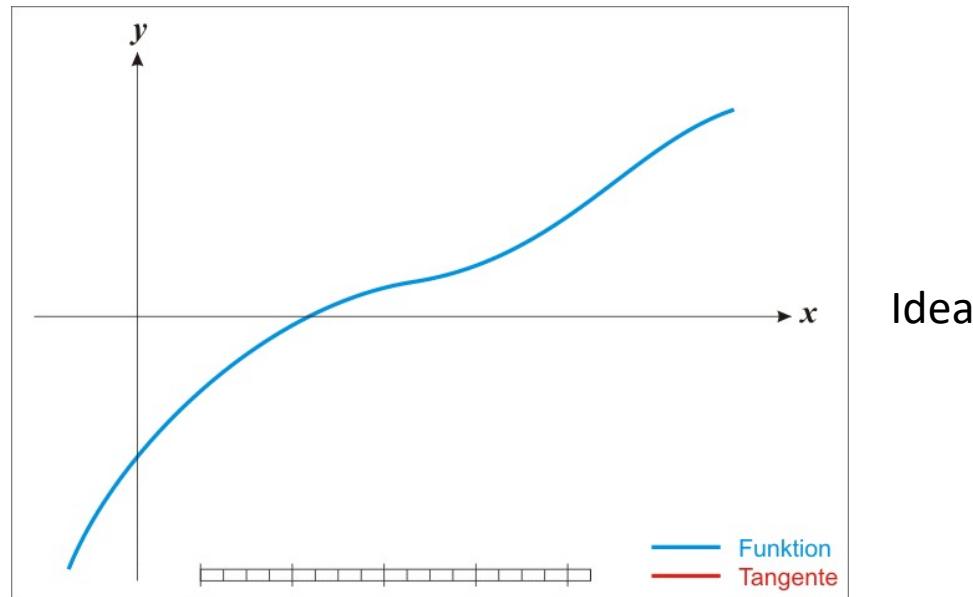
JT = 1/delta*np.array([
    fkine([q1+delta, q2]) - fkine([q1,q2]),
    fkine([q1, q2+delta]) - fkine([q1,q2])])
J = JT.transpose()
print(J)
```

Conclusions

- Inverse kinematics finds joint configurations given a desired position and orientation (pose)
- In inverse kinematics, there can be a single solution, many solutions, infinite solutions, or no solution (the existence of solutions is defined by the workspace)
- Analytic solutions are more complex to find, less systematic and applicable mainly to simple cases
- Numeric solutions are more generic, and they can be applied to all the cases

Appendix I: Newton's Method

- Objective:
 - Find the point where the function is zero
 - Equivalently: find the intersection of the curve $y = f(x)$ with the x axis, that is: $f(x) = 0$



- How?

Imagen de: https://en.wikipedia.org/wiki/Newton%27s_method

Appendix I: Newton's Method

- For scalars (1-D):

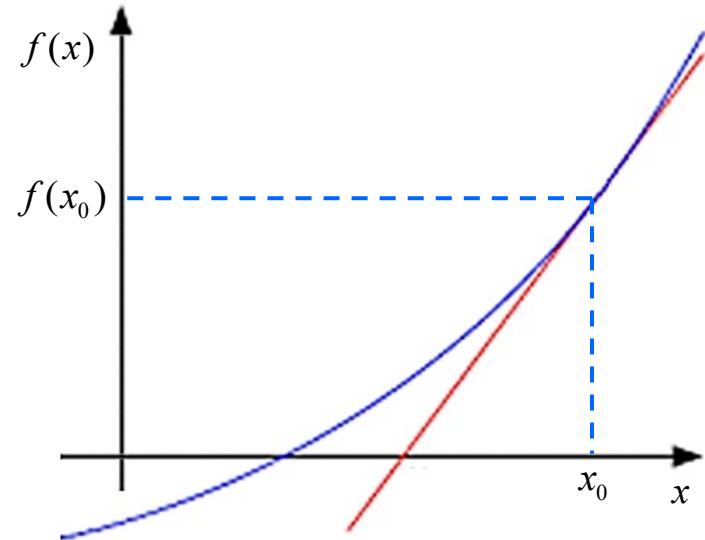
- Tangent line at x_0

- We want the intersection with 0: $f(x) = 0$

$$-f(x_0) = f'(x_0)(x - x_0)$$

- In general:

$$x = x_0 - \frac{f(x_0)}{f'(x_0)}$$



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

Apply iteratively



$x_0, x_1, x_2, x_3, \dots$

- Alternatively: Taylor expansion

$$f(x) = f(x_0) + f'(x_0)(x - x_0) + o(\|x - x_0\|^2)$$

Discarding the high-order terms, we obtain the line equation

High-order terms

Appendix I: Newton's Method

- Example:

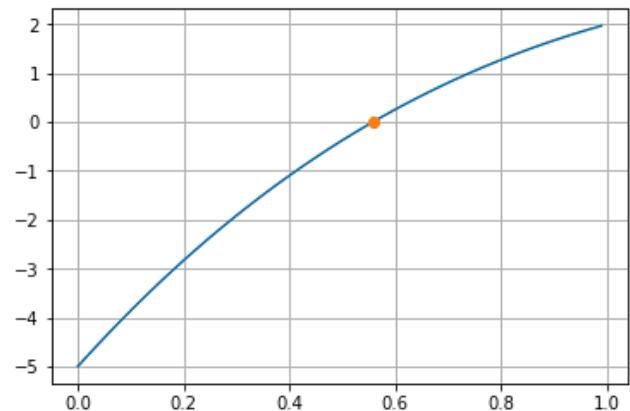
Find the intersection with zero for $f(x) = 3 + (x-2)^3$

$$x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)} \quad \Rightarrow \quad x_{k+1} = x_k - \frac{3 + (x_k - 2)^3}{3(x_k - 2)^2}$$

```
# Initial value (any value)
xo = 0;
# Iterations
for i in range(10):
    xo = xo - (3+(xo-2)**3)/(3*(xo-2)**2)
print('Intersection at: ', str(xo))

# Plot
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt

x = np.arange(0,1,0.01)
y = 3 + (x-2)**3
plt.plot(x,y); plt.plot(xo,0,'o');
plt.grid()
```



Using Python, the
intersection is at: 0.55775