| Robotica Antropomorfa |
| :---: |
| Lezione 10 |
|  |
| os 2205 |

## Back to the global view



## Kinematics

- Kinematics:
- Given the joint angles, compute the hand position

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

- Inverse kinematics:
- Given the hand position, compute the joint angles to attain that position

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

- As usual, inverse problems might be troublesome!


## Representing kinematics

- Representing rotations and translations between coordinate frames of reference

${ }^{A} v=\left[{ }^{A} x_{B}\left|{ }^{A} y_{B}\right|{ }^{A} z_{B}\right]^{B} v={ }^{A} R_{B}{ }^{B} v \quad B \rightarrow A$
${ }^{A} x_{B}={ }^{A} R_{B}{ }^{B} x_{B}={ }^{A} R_{B}[1,0,0]^{T}$

RA 2005

## Kinematics

- Inverting:
- Geometrically: closed form solution exists in certain cases
- By minimization:

$$
J=\frac{1}{2}\|\mathbf{x}-\Lambda(\mathbf{q})\|^{2} \Rightarrow \mathbf{q}=\underset{\mathbf{q}}{\arg \min } J
$$

- Kinematic redundancy: more joints than constraints
- E.g. a rigid body (hand) in space is described by 6 numbers (position + orientation). A robot (or human) arm might have 7 or more joints (degrees of freedom) RA 2005


## Rotation matrix

$$
{ }^{A} R_{B}\left({ }^{A} R_{B}\right)^{T}=I \Leftrightarrow\left({ }^{A} R_{B}\right)^{T}=\left({ }^{A} R_{B}\right)^{-1}={ }^{B} R_{A}
$$

Example: rotation along the $Z$ axis $\left[\begin{array}{ccc}\cos \vartheta & -\sin \vartheta & 0 \\ \sin \vartheta & \cos \vartheta & 0 \\ 0 & 0 & 1\end{array}\right]$


RA 2005

## More simple rotations

Example: rotation along the Y axis $\left[\begin{array}{ccc}\cos \vartheta & 0 & \sin \vartheta \\ 0 & 1 & 0 \\ -\sin \vartheta & 0 & \cos \vartheta\end{array}\right]$

$$
\left[\begin{array}{ccc}
1 & 0 & 0 \\
0 & \cos \vartheta & -\sin \vartheta \\
0 & \sin \vartheta & \cos \vartheta
\end{array}\right]
$$

$$
\text { Example: rotation along the } \mathrm{X} \text { axis }
$$

## Roto-translation

- Rotation combined with translation

$$
{ }^{A} v={ }^{A} R_{B}{ }^{B} v+{ }^{A} O_{B}
$$



## Clearly

$$
\begin{aligned}
& { }^{A} v={ }^{A} T_{B}{ }^{B} T_{C}{ }^{C} v \quad C \rightarrow A \\
& {\left[\begin{array}{cc}
{ }^{A} R_{B} & { }^{A} o_{B} \\
0 & 1
\end{array}\right]=\left[\begin{array}{ccc}
{ }^{A} R_{B}^{T} & -{ }^{A} R_{B}^{T}{ }^{A} o_{B} \\
0 & 1
\end{array}\right]} \\
& { }^{A} T_{B}^{-1}={ }^{B} T_{A}
\end{aligned}
$$

- Composition of transforms
- Inverse of a rototranslation


## Representing 3D rotations

- Sequences of elementary rotations
- Euler angles: z, y, z or z, x, z
- Roll, pitch, yaw angles: $\mathrm{z}, \mathrm{y}, \mathrm{x}$
- Vector (axis of rotation) and angle


## Homogeneous representation

- To make things uniform

$$
\begin{gathered}
{ }^{A} v={ }^{A} R_{B}{ }^{B} V+{ }^{A} O_{B} \\
{\left[\begin{array}{c}
{ }^{A} v \\
1
\end{array}\right]=\left[\begin{array}{cc}
{ }^{A} R_{B} & { }^{A} O_{B} \\
0 & 1
\end{array}\right] \cdot\left[\begin{array}{c}
{ }^{B} v \\
1
\end{array}\right]} \\
{ }^{A} v={ }^{A} T_{B}{ }^{B} v \quad \operatorname{dim}(v)=4 \\
\text { RA 2005 }
\end{gathered}
$$

## Direct kinematics


${ }^{0} T_{1}\left(q_{1}\right) \cdots{ }^{n-1} T_{n}\left(q_{n}\right)$
$(x, y, z)={ }^{0} T_{e}\left(q_{1}, q_{2}, q_{3}, q_{4}\right) \cdot(0,0,0)^{T}$ $\mathbf{x}=\Lambda(\mathbf{q})$
orientation $=\tilde{\Lambda}(\mathbf{q})$

## Conventions

- For placing the reference frames on each link - Denavit-Hartenberg
- Many times DH parameters are given for a manipulator (and various useful equations are also given wrt DH convention)


## Inverse kinematics

- Direct approach
- Try solving:

$$
\begin{aligned}
& x=N L_{x}\left(q_{1}, q_{2}, q_{3}, q_{4}\right) \\
& y=N L_{y}\left(q_{1}, q_{2}, q_{3}, q_{4}\right) \\
& z=N L_{z}\left(q_{1}, q_{2}, q_{3}, q_{4}\right)
\end{aligned}
$$

for $q_{1}, q_{2}, q_{3}, q_{4}$

## Minimization

- Find the solution to:

$$
J=\frac{1}{2}\|\mathbf{x}-\Lambda(\mathbf{q})\|^{2} \Rightarrow \mathbf{q}=\underset{\mathbf{q}}{\arg \min } J
$$

- Neural network/learning:

$$
(\mathbf{q}, \mathbf{x}) \rightarrow \Lambda^{-1}
$$

- Approximate the inverse out of a family of functions (NN approach) starting from examples

RA 2005

## Inverse kinematics

- Direct approach
- Geometric
- Minimization
- Neural network, learning


## Geometric approach

- For certain manipulator the solution exists in close form
- Decomposable structures (e.g. translation and rotations can be handled separately)
- Rotations follow certain rules
- Many industrial manipulators were designed with inverse kinematics in mind


## What about velocity?

- Jacobian matrix

$$
\begin{aligned}
\mathbf{x}=\Lambda(\mathbf{q}) \Rightarrow & \frac{d \mathbf{x} \mathbf{x}}{d t}=\left[\begin{array}{ccc}
\frac{d x_{1}}{d q_{1}} & \cdots & \frac{d x_{1}}{d q_{m}} \\
\vdots & \ddots & \vdots \\
\frac{d x_{n}}{d q_{1}} & \cdots & \frac{d x_{n}}{d q_{m}}
\end{array}\right] \cdot \frac{d \mathbf{q}}{d t} \\
\frac{d \mathbf{x}}{d t} & =\underset{\text { RA 2005 }}{J(\mathbf{q}) \cdot \frac{d \mathbf{q}}{d t}}
\end{aligned}
$$

## Note on representing velocities

- If $\mathbf{x}$ is:

$$
\mathbf{x}=(x, y, z, \vartheta, \varphi, \psi)
$$

- Position + Euler angles

$$
\mathbf{v}=\left(v_{x}, v_{y}, v_{z}, \dot{\vartheta}, \dot{\varphi}, \dot{\psi}\right)
$$

- Euler angles derivatives do not have any clear physical meaning

$$
\mathbf{v}=\left(v_{x}, v_{y}, v_{z}, \boldsymbol{\omega}\right)
$$

- Angular velocity (rate of rotation along the axis


## Jacobian

- Formula
- Given the DH representation of transformations
- Considering only rotational joints

$$
\begin{gathered}
J_{v}=\left[J_{1} \mid J_{2} \cdots J_{n}\right] \\
\text { for } n \text { joints } \\
J_{i}=\left[\begin{array}{c}
{ }^{o} z_{i} \times{ }^{o} p_{E, i} \\
{ }^{o} z_{i}
\end{array}\right] \\
{ }^{o} p_{E, i}={ }^{o} p_{E}-{ }^{o} p_{i}
\end{gathered}
$$

## Anyway...

- Just make sure the representation and the equations are consistent

$$
\begin{gathered}
\mathbf{v}=\left(v_{x}, v_{y}, v_{z}, \dot{v}, \dot{\varphi}, \dot{\psi}\right) \Rightarrow J_{r} \\
\mathbf{v}=\left(v_{x}, v_{y}, v_{z}, \boldsymbol{\omega}\right) \Rightarrow J_{v}
\end{gathered}
$$

## Having written

$$
\begin{gathered}
{ }^{0} T_{i}=\left[\begin{array}{cccc}
{ }^{0} x_{i} & { }^{0} y_{i} & { }^{0} z_{i} & { }^{0} p_{i} \\
0 & 0 & 0 & \\
1
\end{array}\right] \\
{ }^{0} T_{i}={ }^{0} T_{1}{ }_{1} T_{2} \ldots{ }^{i-1} T_{i}
\end{gathered}
$$

## When J is invertible

- Can compute the joint velocities to obtain a certain hand velocity

$$
\dot{\mathbf{q}}=J^{-1} \dot{\mathbf{x}}
$$

- If $n>6$, redundancy:

$$
\dot{\mathbf{q}}=J^{+} \dot{\mathbf{x}}+\left(I-J^{+} J\right) \mathbf{k}
$$

- $\mathbf{k}$ is a constant vector



## Another idea

$$
\boldsymbol{\tau}=J^{T} \mathbf{F}
$$

- Use this equation to design a force controller:
- Given F compute the torques to drive the


## Static

- Relationship between forces and torques

$$
\begin{aligned}
& d \mathbf{x}=J d \mathbf{q} \\
& d \mathbf{q}^{T} \boldsymbol{\tau}=d \mathbf{x}^{T} \mathbf{F} \\
& d \mathbf{q}^{T} \boldsymbol{\tau}=d \mathbf{q}^{T} J^{T} \mathbf{F} \\
& \Downarrow \\
& \boldsymbol{\tau}=J^{T} \mathbf{F}
\end{aligned}
$$

- Imagining the integrals where appropriate


## Dynamics

- Two methods to derive the equation of motion (differential equations)
- Newton-Euler
- Lagrange formalism
joints


## Newton-Euler

- Start from:

$$
\left\{\begin{array}{l}
\mathbf{F}=\frac{d}{d t}(m \mathbf{v}) \\
\boldsymbol{\tau}=\frac{d}{d t}(I \boldsymbol{\omega})
\end{array}\right.
$$

$$
\left\{\begin{array}{c}
\mathbf{F}=\frac{d}{d t}(m \mathbf{v}) \\
\boldsymbol{\tau}=\frac{d}{d t}(I \boldsymbol{\omega})=\boldsymbol{\omega} \times(I \boldsymbol{\omega})+I \dot{\boldsymbol{\omega}} \quad \square \\
\text { kinematics }
\end{array}\right.
$$

RA 2005

| Newton-Euler |  |
| :---: | :---: |
| - Start from: $\left\{\begin{array}{l}\mathbf{F}=\frac{d}{d t}(m \mathbf{v}) \\ \boldsymbol{\tau}=\frac{d}{d t}(I \boldsymbol{\omega})\end{array}\right.$ |  |
|  |  |
|  |  |

## Lagrange formulation

- Lagrange equations:

$$
\begin{gathered}
\left\{\begin{array}{c}
L=K-P \\
\sum_{\mu} F_{\mu} \frac{\partial x_{\mu}}{\partial q_{i}}=\frac{d}{d t}\left(\frac{\partial L}{\partial \dot{q}_{i}}\right)-\frac{\partial L}{\partial q_{i}}
\end{array} \quad x_{\mu}=x_{\mu}\left(q_{1} \cdots q_{N}, t\right)\right. \\
\substack{\text { External forces } \\
\text { (no potential) }}
\end{gathered} K=\frac{1}{2} m \mathbf{v}^{T} \mathbf{v}+\frac{1}{2} \boldsymbol{\omega}^{T} I \boldsymbol{\omega}
$$

RA 2005

## For a manipulator

- Take the joint angles as variable, write the position $x$ of the links, write down K, P and the external forces



## Complexity

- Newton-Euler: $o(n)$
- Lagrange: $o\left(n^{4}\right)$


## Estimation

- Kinematics $\rightarrow$ just measure the params
- Dynamics $\rightarrow$ estimate from data


## Dynamics and control

- Case 1: parameters are such that feedback gain at each joint is >> gravity, Coriolis, centrifugal, disturbances, etc.
- Case 2: feedback in not enough for highspeed, precision, etc. $\rightarrow$ compensation is required


## Dynamics

- Direct dynamics:

$$
\tau(t) \rightarrow q(t)
$$

- Simulation (integrate the equations -Runge-Kutta, Euler, etc.)
- Inverse dynamics:

$$
q(t) \rightarrow \tau(t)
$$

## Case 1

- Approx behavior:

$$
A \ddot{\mathbf{q}}+B \dot{\mathbf{q}}+k\left[\mathbf{q}-\mathbf{q}^{*}\right]=0
$$

- Can design $k$ or a PID controller to make this system behave as desired


## Case 2

- Let's imagine we know all the parameters with a certain precision:

$$
\begin{gathered}
\tau=M(\mathbf{q}) \ddot{\mathbf{q}}+h(\mathbf{q}, \dot{\mathbf{q}}) \dot{\mathbf{q}}+g(\mathbf{q}) \\
\boldsymbol{\tau}_{\text {control }}=M(\mathbf{q}) \mathbf{u}+h(\mathbf{q}, \dot{\mathbf{q}}) \dot{\mathbf{q}}+g(\mathbf{q}) \\
M(\mathbf{q}) \ddot{\mathbf{q}}+h(\mathbf{q}, \dot{\mathbf{q}}) \dot{\mathbf{q}}+g(\mathbf{q})=M(\mathbf{q}) \mathbf{u}+h(\mathbf{q}, \dot{\mathbf{q}}) \dot{\mathbf{q}}+g(\mathbf{q}) \\
M(\mathbf{q}) \ddot{\mathbf{q}}=M(\mathbf{q}) \mathbf{u} \\
\mathbf{u}=\ddot{\mathbf{q}}^{*}+k_{d}\left(\dot{\mathbf{q}}^{*}-\dot{\mathbf{q}}\right)+k_{p}\left(\mathbf{q}^{*}-\mathbf{q}\right) \\
\text { RA } 2005
\end{gathered}
$$

| Case $2($ continued $)$ |  |
| :---: | :---: |
| $\ddot{\mathbf{q}}=\mathbf{u}$ <br> $\mathbf{u}=\ddot{\mathbf{q}}^{*}+k_{d}\left(\dot{\mathbf{q}}^{*}-\dot{\mathbf{q}}\right)+k_{p}\left(\mathbf{q}^{*}-\mathbf{q}\right)$ <br> $\ddot{\mathbf{q}}=\ddot{\mathbf{q}}^{*}+k_{d}\left(\dot{\mathbf{q}}^{*}-\dot{\mathbf{q}}\right)+k_{p}\left(\mathbf{q}^{*}-\mathbf{q}\right)$ <br> $\mathbf{e}=\mathbf{q}^{*}-\mathbf{q}$ <br> $0=\ddot{\mathbf{e}}+k_{d} \dot{\mathbf{e}}+k_{p} \mathbf{e}$ | t |
| Appropriate design of the gains can get <br> arbitrary exponential behavior of the error |  |
| RA 2005 |  |

