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***Wear**able **DY**namics*

Force and motion capture system based on distributed micro-accelerometers, gyros, force and tactile sensing

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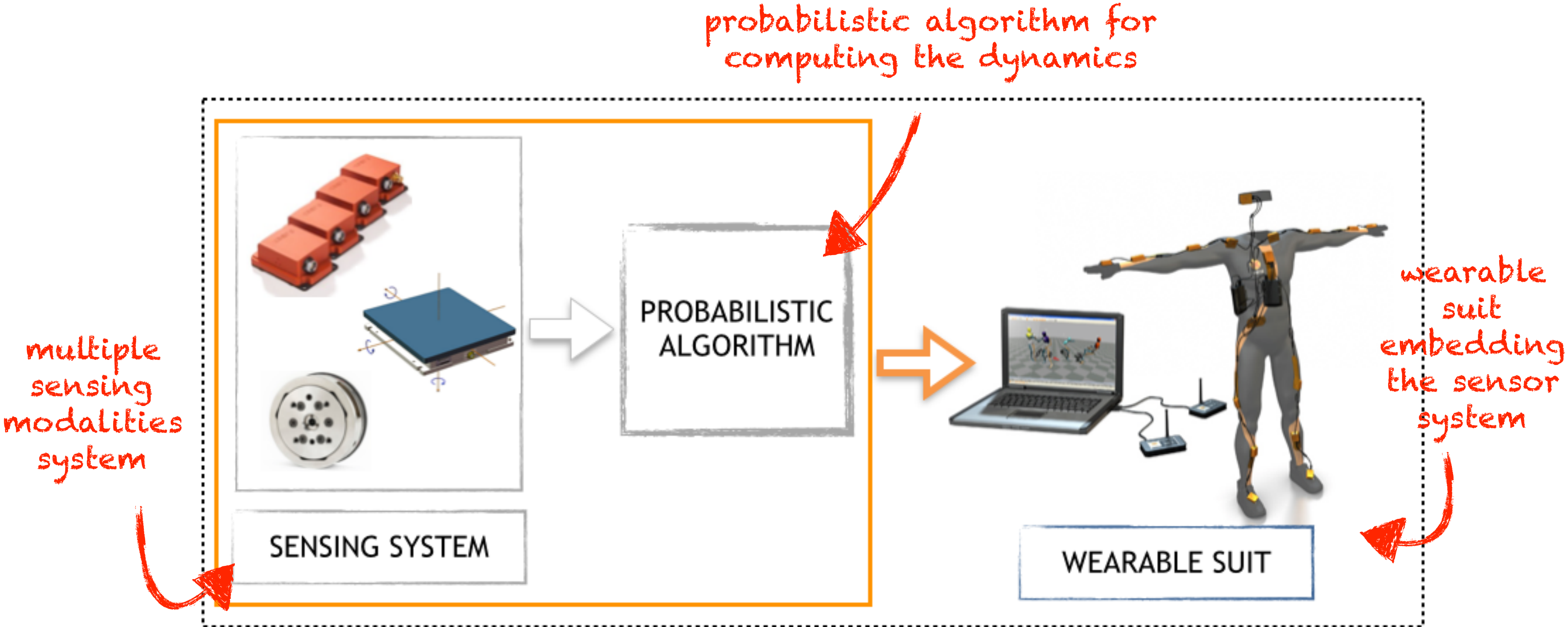
Why

Human body is able to adapt movements according to an internal perception of the body itself with respect to external environment. From a physical point of view the better way to approach the problem is to have information on the dynamics of the body by measuring kinematics and dynamics quantities in order to obtain the best estimation of forces and torques.

Knowing dynamic information in human motion is a crucial point in several research areas such as ergonomics for industrial scenarios, rehabilitation monitoring or for developing prosthetic devices and exoskeleton systems.

What is *WearDY*?



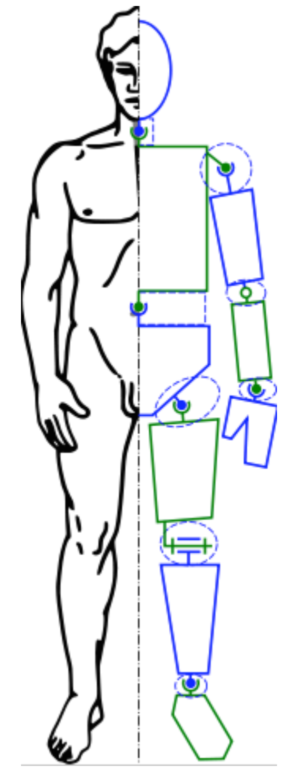
A system capable of detecting simultaneously both kinematics and dynamics quantities harnessing redundant measurements information coming from sensors and from a-priori knowledge of the system itself

Human Inverse Dynamics

Powerful analytical tool used in biomechanics analysis for computing joint torques

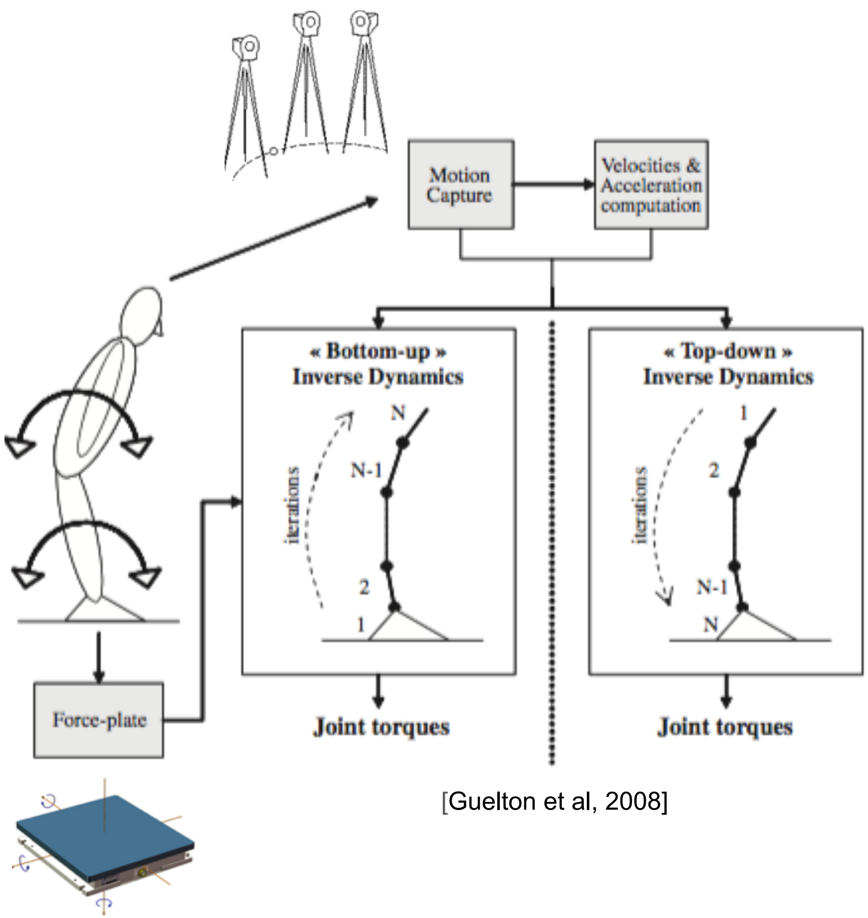
Kinematics, dynamics and anthropometric information are considered as inputs

Sensitive and complex problem passing from robotic control problem to the human motion case



Classical Inverse Dynamics Approach

Joint torques have been estimated using two different approaches:



[Guelton et al, 2008]

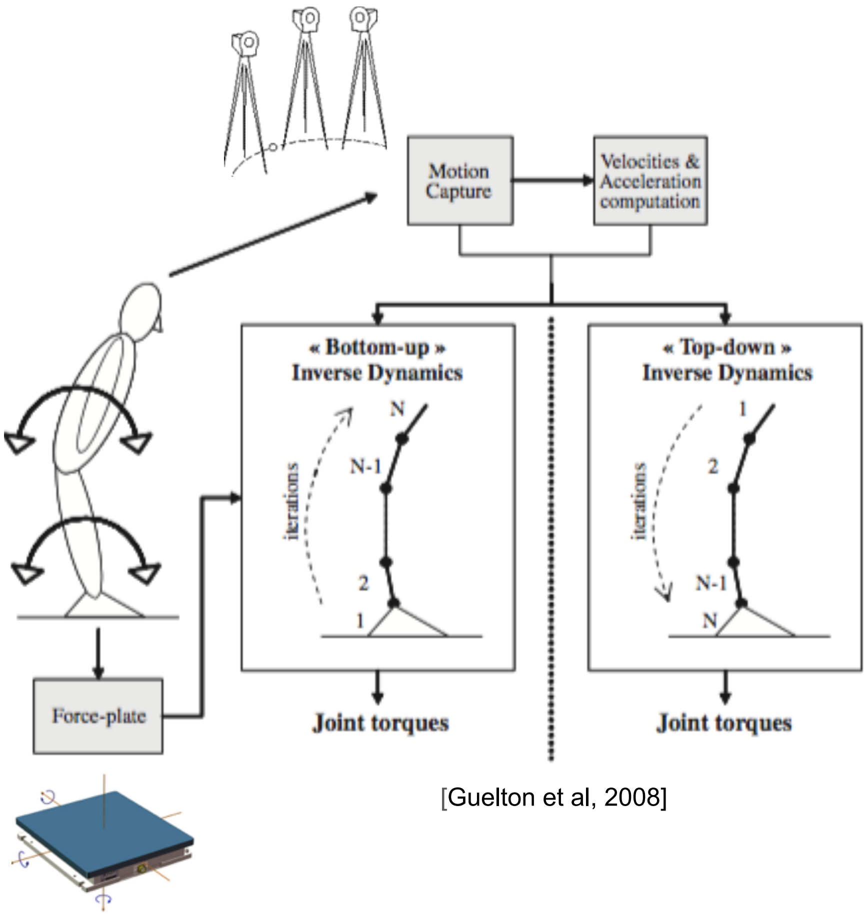
"*Top-down*"

[…] **needs the angular positions, velocities and acceleration measurements** and/or estimations to compute joint torques […].

"*Bottom-up*"

[…], **in addition to angular positions, velocities and accelerations measurements** and/or computations, […] **also requires the external forces measurements**.

Classical Inverse Dynamics Approach



[Guelton et al, 2008]

"*Top-down*"

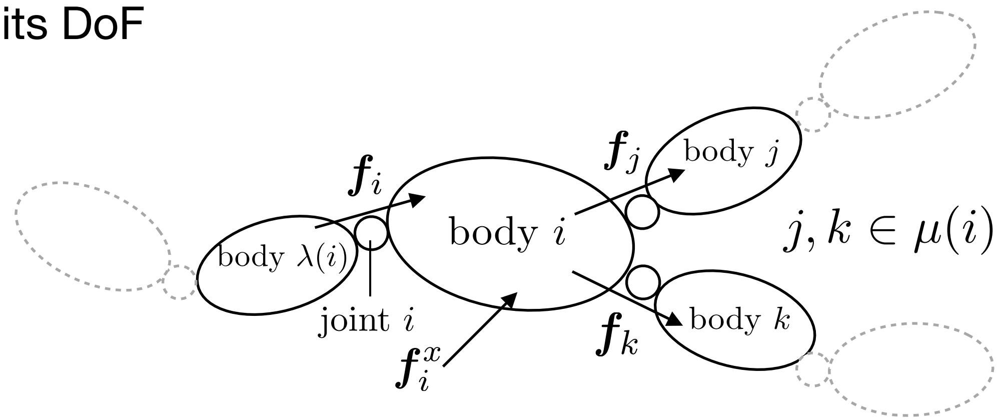
more sensitive to noise propagation since its robustness is strongly related to the accuracy of the input data

"*Bottom-up*"

less sensitive to noise propagation, but it leads to an over-determined system since at the top-most link the physics condition are not satisfied anymore

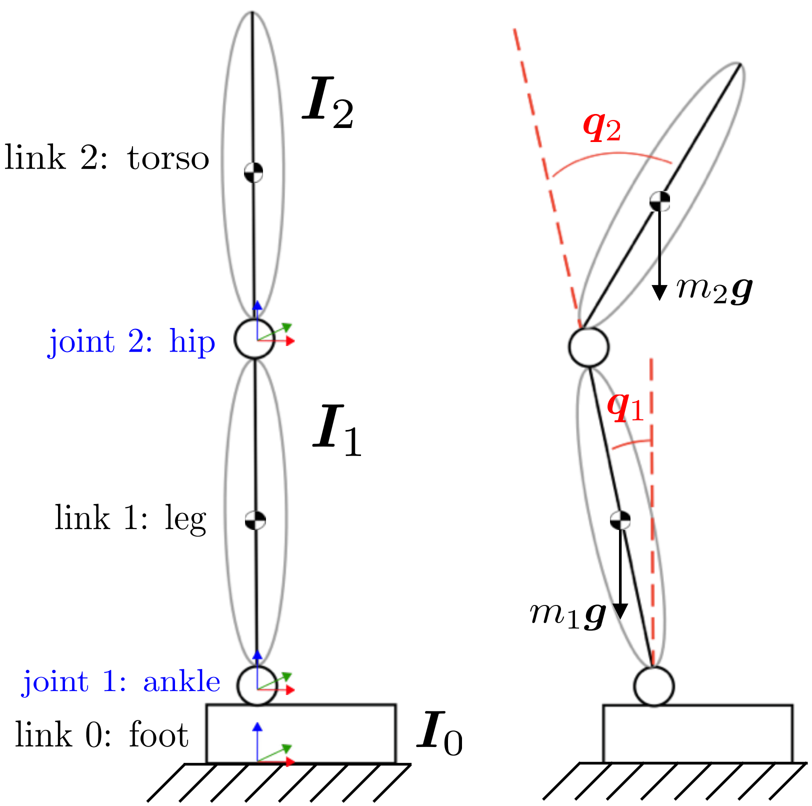
Spatial algebra notation

- Variables are *spatial* vectors (six dimensional vectors including angular quantities in the first three components and the rest as linear quantities)
- Rigid body system described as an oriented kinematic tree with n Degrees-of-Freedom (DoF) and N_B links (numbering from 0 to N_B)
- Links i and its parent λ_i are coupled with joint *i*
- Joint *i* motion freedom subspace is modeled with $\boldsymbol{S}_i \in \mathbb{R}^{6 \times n_i}$ being n_i its DoF



Link quantities	Joint quantities
$\boldsymbol{v}_i$ $\boldsymbol{a}_i$ $\boldsymbol{I}_i$ $\boldsymbol{f}_i$ $\boldsymbol{f}_i^B$ $\boldsymbol{f}_i^x$	$\boldsymbol{q}_i$ $\dot{\boldsymbol{q}}_i$ $\ddot{\boldsymbol{q}}_i$ $\boldsymbol{v}_{Ji}$ $\boldsymbol{\tau}_i$

Human body modeling



$N_B = 2, \quad \boldsymbol{d} \in \mathbb{R}^{40}$

Dynamic variables of each link are properly clustered in the ***link-related dynamics variables vector*** $\boldsymbol{d}$

$$\boldsymbol{d} = \begin{bmatrix} \boldsymbol{d}_1 \\ \boldsymbol{d}_2 \\ \vdots \\ \boldsymbol{d}_{N_B} \end{bmatrix} \in \mathbb{R}^{18N_B+n}$$

$$\boldsymbol{d}_i = \begin{bmatrix} \boldsymbol{a}_i^\top \\ \boldsymbol{f}_i^\top \\ \boldsymbol{\tau}_i \\ \boldsymbol{f}_i^{x\top} \\ \ddot{q}_i \end{bmatrix} \in \mathbb{R}^{18+n_i}$$

Dynamical consistency and measurement equation

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$$\boldsymbol{a}_i = {}^i\boldsymbol{X}_{\lambda(i)}\boldsymbol{a}_{\lambda(i)} + \boldsymbol{S}_i\ddot{\boldsymbol{q}}_i + \boldsymbol{v}_i \times \boldsymbol{v}_{Ji}$$

$$\boldsymbol{f}_i = \underbrace{\boldsymbol{I}_i\boldsymbol{a}_i + \boldsymbol{v}_i \times^* \boldsymbol{I}_i\boldsymbol{v}_i}_{\boldsymbol{f}_i^B} - {}^i\boldsymbol{X}_0^*\boldsymbol{f}_i^x + \sum_{j\in\mu(i)} {}^i\boldsymbol{X}_j^*\boldsymbol{f}_j$$

where:

$$\boldsymbol{v}_i = {}^i\boldsymbol{X}_{\lambda(i)}\boldsymbol{v}_{\lambda(i)} + \boldsymbol{v}_{Ji},$$

$$\boldsymbol{v}_{Ji} = \boldsymbol{S}_i\dot{\boldsymbol{q}}_i$$

Dynamical consistency of the system

$$\boldsymbol{D}(\boldsymbol{q},\dot{\boldsymbol{q}})\boldsymbol{d} + \boldsymbol{b}_D(\boldsymbol{q},\dot{\boldsymbol{q}}) = \boldsymbol{0}$$

$$\boldsymbol{y}_{i,acc} = ({}^S\boldsymbol{X}_i\boldsymbol{a}_i)_l + ({}^S\boldsymbol{X}_i\boldsymbol{v}_i)_a \times ({}^S\boldsymbol{X}_i\boldsymbol{v}_i)_l,$$

$$\boldsymbol{y}_{i,gyr} = {}^S\boldsymbol{R}_i(\boldsymbol{v}_i)_a,$$

$$\boldsymbol{y}_{fpl} = {}^S\boldsymbol{X}_0{}^*(\boldsymbol{f}_1 + \boldsymbol{I}_0\boldsymbol{a}_0 + \boldsymbol{v}_0 \times^* \boldsymbol{I}_0\boldsymbol{v}_0)$$

Measurements equation

$$\boldsymbol{Y}(\boldsymbol{q},\dot{\boldsymbol{q}})\boldsymbol{d} + \boldsymbol{b}_Y(\boldsymbol{q},\dot{\boldsymbol{q}}) = \boldsymbol{y}.$$

Dynamic system considering redundant measurements :

$$\begin{bmatrix}\boldsymbol{D}(\boldsymbol{q},\dot{\boldsymbol{q}})\\ \boldsymbol{Y}(\boldsymbol{q},\dot{\boldsymbol{q}})\end{bmatrix}\boldsymbol{d} + \begin{bmatrix}\boldsymbol{b}_D(\boldsymbol{q},\dot{\boldsymbol{q}})\\ \boldsymbol{b}_Y(\boldsymbol{q},\dot{\boldsymbol{q}})\end{bmatrix} = \begin{bmatrix}\boldsymbol{0}\\ \boldsymbol{y}\end{bmatrix}$$

Maximum-a-Posteriori (MAP) Estimator

Probabilistic framework: estimate $\boldsymbol{d}$ given $\boldsymbol{y}$

$$p(\boldsymbol{d}|\boldsymbol{y}) = \frac{p(\boldsymbol{d},\boldsymbol{y})}{p(\boldsymbol{y})} \Rightarrow p(\boldsymbol{d},\boldsymbol{y}) = p(\boldsymbol{d})p(\boldsymbol{y}|\boldsymbol{d})$$

Building the probability density for each term of the joint probability:

$$\boldsymbol{Y}(\boldsymbol{q},\dot{\boldsymbol{q}})\boldsymbol{d} + \boldsymbol{b}_Y(\boldsymbol{q},\dot{\boldsymbol{q}}) = \boldsymbol{y}.$$

$$p(\boldsymbol{y}|\boldsymbol{d}) \sim \mathcal{N}(\boldsymbol{\mu}_y, \boldsymbol{\Sigma}_y), \quad \boldsymbol{\mu}_y = \boldsymbol{Y}\boldsymbol{d} + \boldsymbol{b}_Y$$

$$p(\boldsymbol{y}|\boldsymbol{d}) \propto \exp -\frac{1}{2}\left\{(\boldsymbol{y}-\boldsymbol{\mu}_y)^\top \boldsymbol{\Sigma}_y^{-1}(\boldsymbol{y}-\boldsymbol{\mu}_y)\right\}$$

$$\boldsymbol{D}(\boldsymbol{q},\dot{\boldsymbol{q}})\boldsymbol{d} + \boldsymbol{b}_D(\boldsymbol{q},\dot{\boldsymbol{q}}) = \boldsymbol{0}$$

$$p(\boldsymbol{d}) \propto \exp -\frac{1}{2}\left\{\boldsymbol{e}(\boldsymbol{d})^\top \boldsymbol{\Sigma}_D^{-1}\boldsymbol{e}(\boldsymbol{d}) + (\boldsymbol{d}-\boldsymbol{\mu}_d)^\top \boldsymbol{\Sigma}_d^{-1}(\boldsymbol{d}-\boldsymbol{\mu}_d)\right\}$$

$$\boldsymbol{\Sigma}_{d|y} = \left(\bar{\boldsymbol{\Sigma}}_D^{-1} + \boldsymbol{Y}^\top \boldsymbol{\Sigma}_y^{-1}\boldsymbol{Y}\right)^{-1},$$

$$\boldsymbol{\mu}_{d|y} = \boldsymbol{\Sigma}_{d|y}\left[\boldsymbol{Y}^\top \boldsymbol{\Sigma}_y^{-1}(\boldsymbol{y}-\boldsymbol{b}_Y) + \bar{\boldsymbol{\Sigma}}_D^{-1}\bar{\boldsymbol{\mu}}_D\right]$$

On the benefit of MAP estimation

$$\boldsymbol{\Sigma}_{d|y} = \left(\boldsymbol{D}^\top \boldsymbol{\Sigma}_D^{-1} \boldsymbol{D} + \boldsymbol{\Sigma}_d^{-1} + \boldsymbol{Y}^\top \boldsymbol{\Sigma}_y^{-1} \boldsymbol{Y}\right)^{-1}$$

If we add multiple measurements $\boldsymbol{y}_1 = \boldsymbol{Y}_1 \boldsymbol{d} + \boldsymbol{b}_{Y_1}, \ldots, \boldsymbol{y}_m = \boldsymbol{Y}_m \boldsymbol{d} + \boldsymbol{b}_{Y_m}$

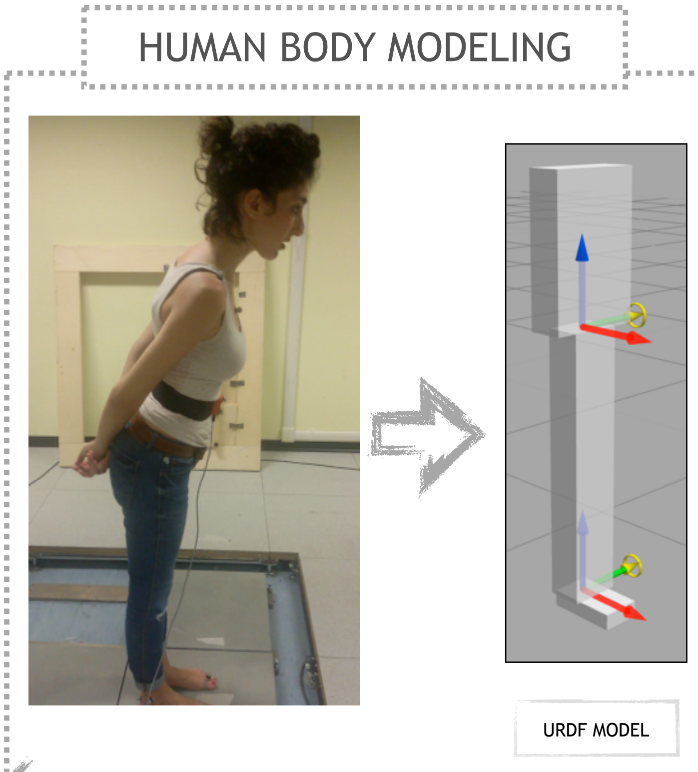
$$\boldsymbol{Y}^\top \boldsymbol{\Sigma}_y^{-1} \boldsymbol{Y} = \begin{bmatrix} \boldsymbol{Y}_1^\top & \ldots & \boldsymbol{Y}_m^\top \end{bmatrix} \begin{bmatrix} \boldsymbol{\Sigma}_{y_1}^{-1} & \ldots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \ldots & \boldsymbol{\Sigma}_{y_m}^{-1} \end{bmatrix} \begin{bmatrix} \boldsymbol{Y}_1 \\ \vdots \\ \boldsymbol{Y}_m \end{bmatrix}$$

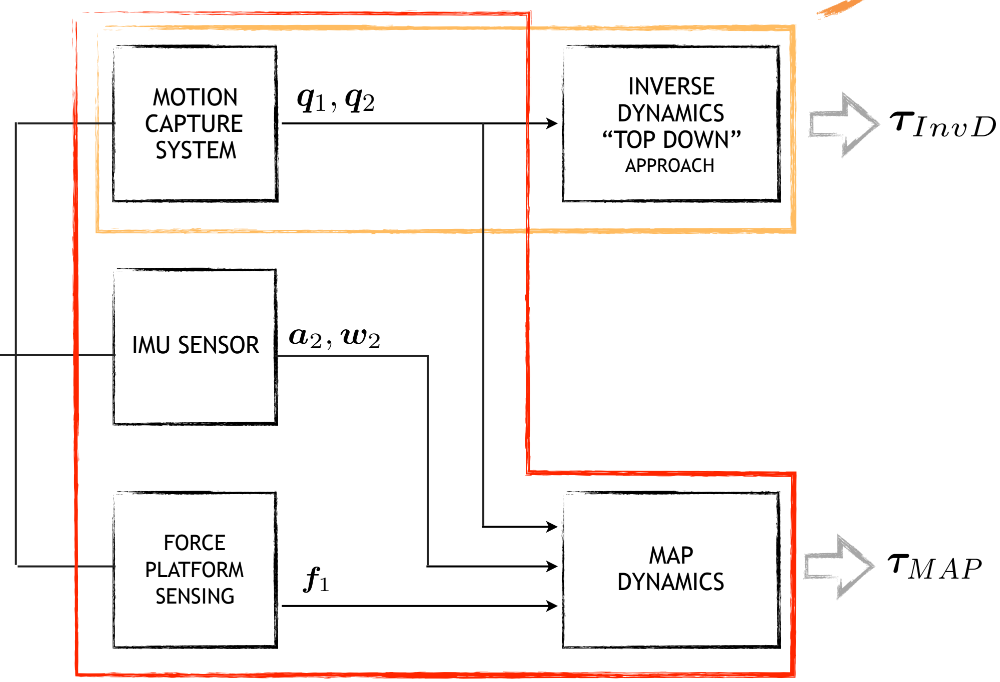
the addition of each measurement induces changes in the associated covariance matrix decreasing at each step the uncertainty in the estimation according to

$$\boldsymbol{\Sigma}_{d|y_i}^{-1} = \boldsymbol{\Sigma}_{d|y_{i-1}}^{-1} + \boldsymbol{Y}_i^\top \boldsymbol{\Sigma}_{y_i}^{-1} \boldsymbol{Y}_i$$

WearDY preliminary test

Newton-Euler algorithm provides a reference benchmark to compare forthcoming MAP sensor fusion analysis



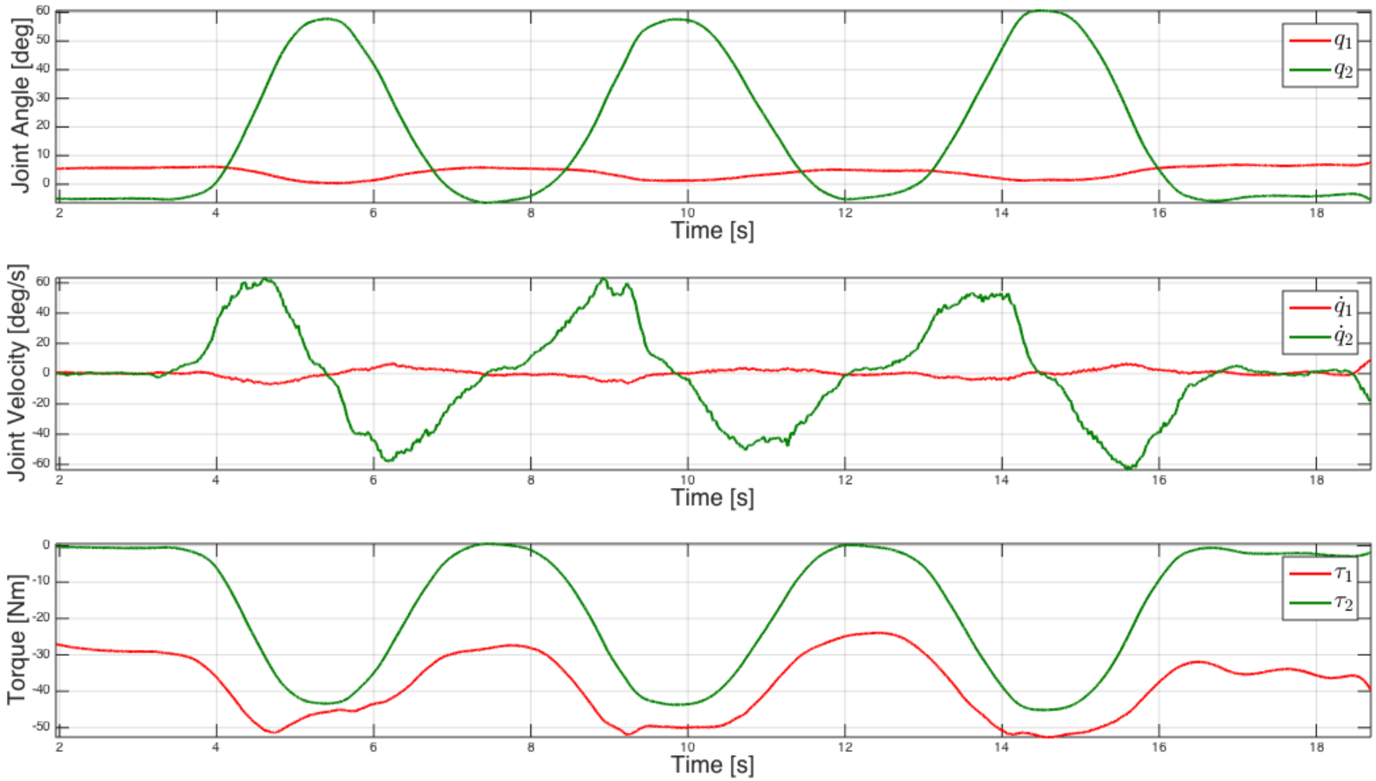


Subject body parameters have been used to build a URDF model as input for the system

MAP estimation will take into account the redundant measurements coming from sensor

WearDY preliminary test

Testing Inverse Dynamics benchmark



Forthcoming works

- ✓ Experimental validation of theoretical MAP dynamics
- ✓ Integrate *WearDY* in an Kalman filter-like class combining obtained *a-posteriori* estimate with *a-priori* estimate of the filter state
- ✓ Developing a prototype of sensing shoes replacing the force platform
- ✓ Including EMG analysis