Introduction to the Stack Of Tasks
A framework for flexible whole-body control of humanoid robots

International Winter School on Humanoid Robot Programming

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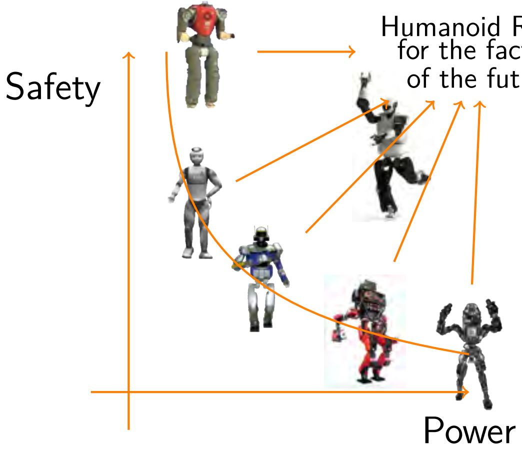
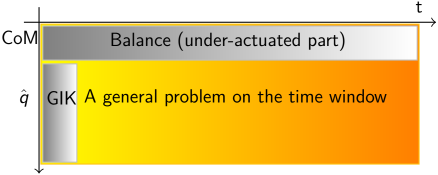
Acknowledgements

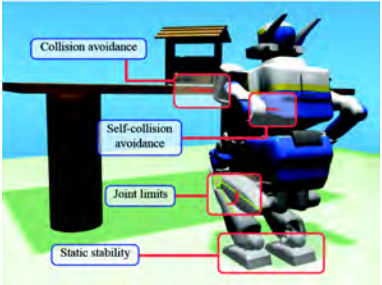
Testing our algorithms in real industrial use case



Motion generation: the problem

$$
\begin{cases}
\min f(\mathbf{u}(t), \mathbf{v}(t)) \\
\mathbf{g}(\mathbf{u}(t), \mathbf{v}(t)) < 0 \\
\mathbf{h}(\mathbf{u}(t), \mathbf{v}(t)) = 0
\end{cases}
$$





SDKs

- Gepetto is developping Software Development Kits
- Stack Of Tasks
- Humanoid Path Planner

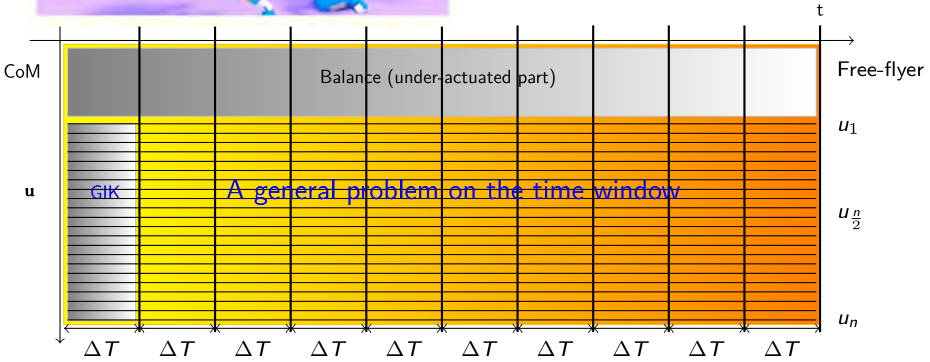
- Try to identify software patterns from the problem formulation
- Write our own solvers when needed (often)
- Be as much generic as possible
- Fragment the code
- Integration through a build farm with binairies (robotpkg)

Motion generation

- Size of the problem

$$2 \times 200 \times 30 = 9600 \text{ variables}$$

- Non linear constraints
- Discrete nature due to contacts

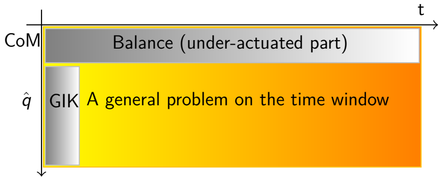


MuJoCo [Koenemann, IROS 2015]

https://www.youtube.com/watch?v=WbsQBPzQakc

Motion generation

$$\begin{cases} \min f(\mathbf{u}(t), \mathbf{v}(t)) \\ \mathbf{g}(\mathbf{u}(t), \mathbf{v}(t)) < 0 \\ \mathbf{h}(\mathbf{u}(t), \mathbf{v}(t)) = 0 \end{cases}$$



- Planning and control solve the same problem
  - Planning is looking for a global feasible solution
  - Control is looking for on online sensor grounded local solution
- Planning is too long when simulating the control
- Control can fails
  - Local minima leading to an incomplete behavior
  - Mismatch between the control and the hardware
- Accessibility set [Majumdar, ICRA Best Paper Award 2013]

HPP [IJRR Submitted]

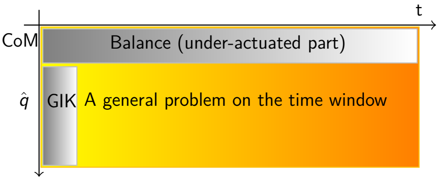
http://stevetonneau.fr/files/publications/ijrr16/video.mp4

Take away messages

- The *embodiment* (mechanical body, limits and controllers) defines the motion capabilities of the robot.
- We need to connect the accessibility set of our controllers to the planner.
- We need an efficient computation of the mechanical quantities
- We need to break down the problem complexity with small but representative problems
- We need to push higher the semantic level of our motion controllers

Motion generation

$$\begin{cases} \min f(\mathbf{u}(t), \mathbf{v}(t)) \\ \mathbf{g}(\mathbf{u}(t), \mathbf{v}(t)) < 0 \\ \mathbf{h}(\mathbf{u}(t), \mathbf{v}(t)) = 0 \end{cases}$$

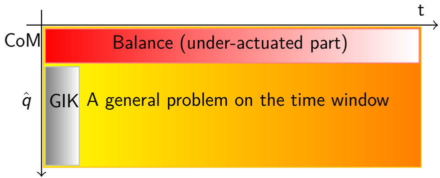


$$\begin{cases} \mathbf{M}_1(q)\ddot{q} + \mathbf{N}_1(q,\dot{q})\dot{q} + \mathbf{G}_1(q) = \mathbf{T}_1(\mathbf{q})\mathbf{u} + \mathbf{C}_1^\top(q)\lambda & \text{Actuated dynamics of the robot} \\ \mathbf{M}_2(q)\ddot{q} + \mathbf{N}_2(q,\dot{q})\dot{q} + \mathbf{G}_2(q) = \mathbf{C}_2^\top(q)\lambda & \text{Underactuated dynamics of the robot} \\ f(\lambda) \in \mathcal{F} & \text{General balance criteria} \\ \mathbf{u}_{min} < \mathbf{u} < \mathbf{u}_{max} & \text{Torques limits} \\ \hat{q}_{min} < \hat{q} < \hat{q}_{max} & \text{Joints limits} \\ d(\mathcal{B}_i(\mathbf{q}), \mathcal{B}_j(\mathbf{q})) > \epsilon, \forall p(i,j) \in \mathcal{P} & \text{(self-)collisions} \\ \ddot{\mathbf{e}}_i = \dot{\mathbf{J}}_i(q)\dot{q} + \mathbf{J}_i(q)\ddot{q} & \text{Tasks} \end{cases}$$

Motion generation

Pattern generator

- Focus on the underactuated part
- Model predictive control



Simplifying the walking problem to control only the CoM reference

$$
\begin{cases}
\mathbf{M}_1(q)\ddot{q} + \mathbf{N}_1(q,\dot{q})\dot{q} + \mathbf{G}_1(q) = \mathbf{T}_1(\mathbf{q})\mathbf{u} + \mathbf{C}_1^\top(q)\lambda & \text{Actuated dynamics of the robot} \\
\mathbf{M}_2(q)\ddot{q} + \mathbf{N}_2(q,\dot{q})\dot{q} + \mathbf{G}_2(q) = \mathbf{C}_2^\top(q)\lambda & \text{Underactuated dynamics of the robot} \\
f(\lambda) \in \mathcal{F} & \text{General balance criteria} \\
\mathbf{u}_{min} < \mathbf{u} < \mathbf{u}_{max} & \text{Torques limits} \\
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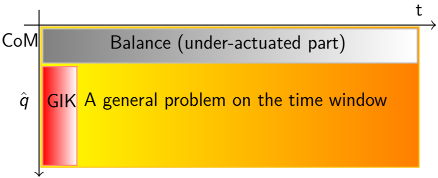
d(\mathcal{B}_i(\mathbf{q}), \mathcal{B}_j(\mathbf{q})) > \epsilon, \forall p(i,j) \in \mathcal{P} & \text{(self-)collisions} \\
\ddot{\mathbf{e}}_i = \dot{\mathbf{J}}_i(q)\dot{q} + \mathbf{J}_i(q)\ddot{q} & \text{Tasks}
\end{cases}
$$

Motion generation

Inverse dynamics

- Focus on the inertia matrix
- Forces
- Complete constraints



$$
\begin{cases}
\mathbf{M}_1(q)\ddot{q} + \mathbf{N}_1(q,\dot{q})\dot{q} + \mathbf{G}_1(q) = \mathbf{T}_1(\mathbf{q})\mathbf{u} + \mathbf{C}_1^\top(q)\lambda & \text{Actuated dynamics of the robot} \\
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\ddot{\mathbf{e}}_i = \dot{\mathbf{J}}_i(q)\dot{q} + \mathbf{J}_i(q)\ddot{q} & \text{Tasks}
\end{cases}
$$

Under actuation

Generalized locomotion Climbing stairs

[Carpentier, ICRA 2016]
[Kudruss, Humanoids 2015]

Previous work
[Luo, ICRA 2014]
[Vaillant, Humanoids 2014]
[Noda, ICRA 2014]
[Hirukawa, ICRA 2007]

$$\left\{ \begin{array}{l} m(\ddot{\mathbf{c}}(\mathbf{u}) - \mathbf{g}) = \sum_{i=1}^{N_c} \mathbf{f}_i, \;\; \lambda_i = [\mathbf{f}_i^\top \mu_i^\top]^\top \\ m\mathbf{c}(\mathbf{u})_\times (\ddot{\mathbf{c}}(\mathbf{u}) - \mathbf{g}) + \mathbf{w}^\top(\mathbf{u})\mathbf{I}\mathbf{w}^\top(\mathbf{u}) = \sum_{i=1}^{N_c} \mathbf{p}_{i\times} \mathbf{f}_i + \mu_i \end{array} \right.$$

Reactive walking pattern generation

Walking without thinking: $(\dot{\mathbf{X}}^{ref}, \dot{\mathbf{Y}}^{ref}, \dot{\theta}^{ref})$[M. Naveau, RA-L 2016]

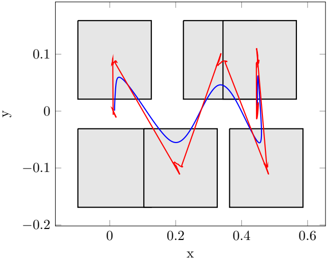
Optimization problem solved:

$$\min_{\mathbf{U}_k} \sum_{i=0}^{j=4} w_i J_i(\mathbf{U}_k)$$

$$\mathbf{X}_{k+1} = \mathbf{A}\mathbf{X}_k + \mathbf{C}\mathbf{U}_k$$

$$\underline{\mathbf{P}} < \mathbf{P}\mathbf{U}_k < \overline{\mathbf{P}}$$

with $\mathbf{U}_k = \left(\dddot{\mathbf{X}}_k \; \mathbf{X}^f_k \; \dddot{\mathbf{Y}}_k \; \mathbf{Y}^f_k \right)^T$



$J_1(\mathbf{U}_k)$ is the linear velocity tracking

$$J_1(\mathbf{U}_k) = \|\dot{\mathbf{X}}_k - \dot{\mathbf{X}}^{ref}_k\|^2_2 + \|\dot{\mathbf{Y}}_k - \dot{\mathbf{Y}}^{ref}_k\|^2_2$$

Reactive walking pattern generation

Walking without thinking: $(\dot{\mathbf{X}}^{ref}, \dot{\mathbf{Y}}^{ref}, \dot{\theta}^{ref})$[M. Naveau, RA-L 2016]

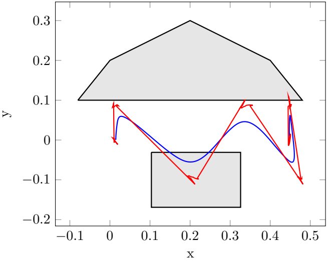
Optimization problem solved:

$$\min_{\mathbf{U}_k} \sum_{i=0}^{j=4} w_i J_i(\mathbf{U}_k)$$

$$\mathbf{X}_{k+1} = \mathbf{A}\mathbf{X}_k + \mathbf{C}\mathbf{U}_k$$

$$\underline{\mathbf{P}} < \mathbf{P}\mathbf{U}_k < \overline{\mathbf{P}}$$

with $\mathbf{U}_k = \left(\dddot{\mathbf{X}}_k \; \mathbf{X}_k^f \; \dddot{\mathbf{Y}}_k \; \mathbf{Y}_k^f\right)^T$



$J_2(\mathbf{U}_k)$ is the control norm

$$J_2(\mathbf{U}_k) = \|\dddot{\mathbf{X}}_k\|_2^2 + \|\dddot{\mathbf{Y}}_k\|_2^2$$

Reactive walking pattern generation

Walking without thinking: $(\dot{\mathbf{X}}^{ref}, \dot{\mathbf{Y}}^{ref}, \dot{\theta}^{ref})$[M. Naveau, RA-L 2016]

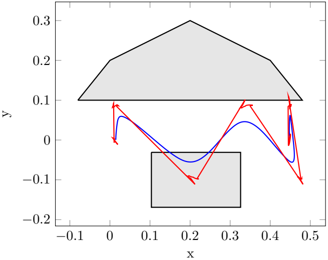
Optimization problem solved:

$$\min_{\mathbf{U}_k} \sum_{i=0}^{j=4} w_i J_i(\mathbf{U}_k)$$

$$\mathbf{X}_{k+1} = \mathbf{A}\mathbf{X}_k + \mathbf{C}\mathbf{U}_k$$

$$\underline{\mathbf{P}} < \mathbf{P}\mathbf{U}_k < \overline{\mathbf{P}}$$

with $\mathbf{U}_k = \left(\dddot{\mathbf{X}}_k \ \mathbf{X}^f_k \ \dddot{\mathbf{Y}}_k \ \mathbf{Y}^f_k \right)^T$



$J_3(\mathbf{U}_k)$ is the distance of the CoP to the most stable trajectory

$$J_3(\mathbf{U}_k) = \|\mathbf{X}^f_k - CoP^x_{k+1}\|^2_2 + \|\mathbf{Y}^f_{k+1} - CoP^y_{k+1}\|^2_2$$

Reactive walking pattern generation with obstacles

Walking without thinking: $(\dot{\mathbf{X}}^{ref}, \dot{\mathbf{Y}}^{ref}, \dot{\theta}^{ref})$[M. Naveau, RA-L 2016]

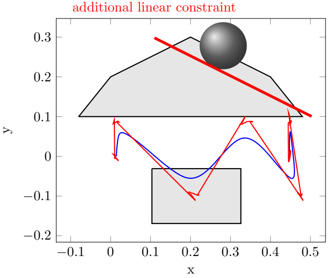
Optimization problem solved:

$$\min_{\mathbf{U}_k} \sum_{i=0}^{j=4} w_i J_i(\mathbf{U}_k)$$

$$\mathbf{X}_{k+1} = \mathbf{A}\mathbf{X}_k + \mathbf{C}\mathbf{U}_k$$

$$\underline{\mathbf{P}} < \mathbf{P}(\mathbf{U}_k)\mathbf{U}_k < \overline{\mathbf{P}}$$

with $\mathbf{U}_k = \left(\dddot{\mathbf{X}}_k \; \mathbf{X}_k^f \; \dddot{\mathbf{Y}}_k \; \mathbf{Y}_k^f \; \theta_k^f\right)^T$



$J_4(\mathbf{U}_k)$ is the angular velocity tracking

$$J_4(\mathbf{U}_k) = \|\theta_k - \int \theta_k^{ref} dt\|_2^2$$

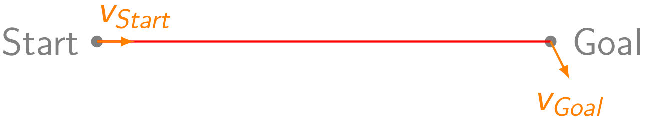
Walking Pattern Generator [RA-L 20

Under actuation: Application

Power Law

Human moves according to the two-third power-law

$$v = \gamma \kappa^{\beta}$$



Power Law

Human moves according to the two-third power-law

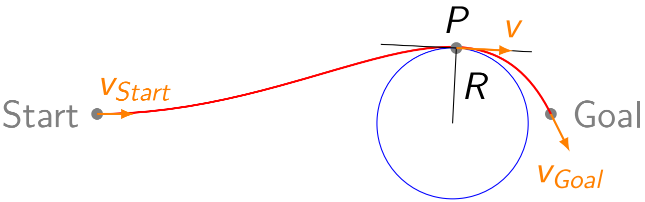
$$\boxed{v} = \gamma \kappa^{\beta}$$

Power Law

Human moves according to the two-third power-law

$$\boxed{v} = \gamma \boxed{\kappa}^{\beta}$$

$$\boxed{\kappa = \frac{1}{R}}$$



Power Law

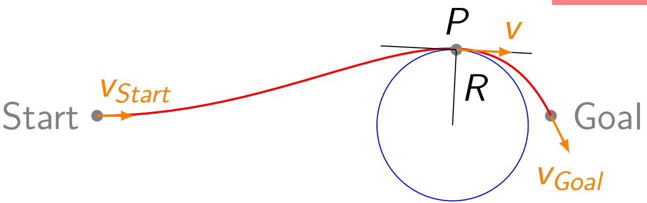
Human moves according to the two-third power-law

$$\boxed{v} = \gamma \kappa^{\boxed{\beta}}$$

$\beta = -1/3$

$\beta = 0$

$\beta = 1/3$

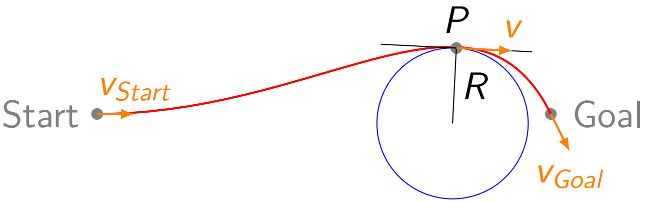


Power Law

Human moves according to the two-third power-law

$$v = \gamma \kappa^{\beta}$$

γ such that time from Start to Goal is always the same $\forall \beta$



Power Law

Human moves according to the two-third power-law

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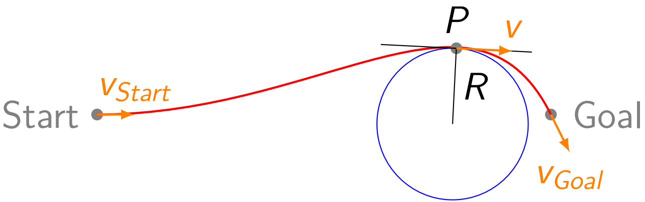

Power Law

Human moves according to the two-third power-law

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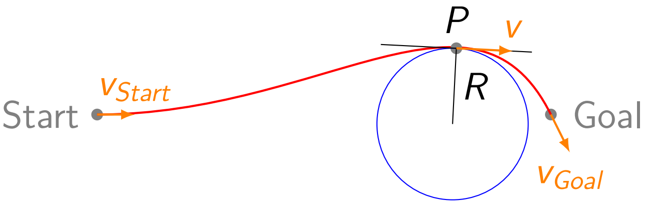
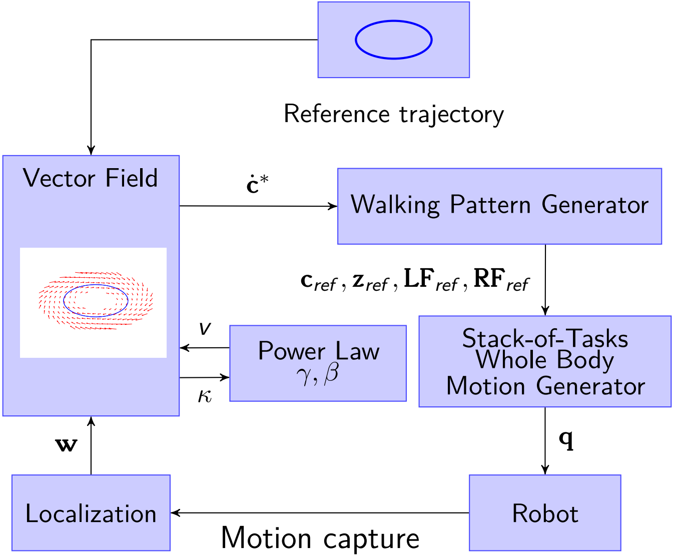


Can humanoid robots benefit from following the same principle ?

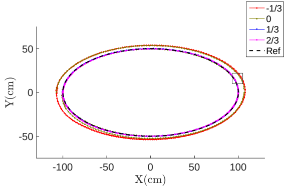
Approach



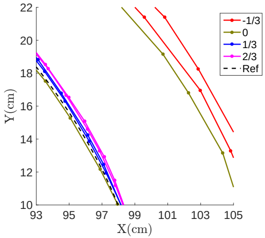
Reference trajectory
Vector Field
$\dot{\mathbf{c}}^*$
Walking Pattern Generator
$\mathbf{c}_{ref}, \mathbf{z}_{ref}, \mathbf{LF}_{ref}, \mathbf{RF}_{ref}$
v
Power Law
γ, β
κ
Stack-of-Tasks
Whole Body
Motion Generator
$\mathbf{q}$
$\mathbf{w}$
Localization
Robot
Motion capture

Mixing NMPC walking and Power Law: Results

- Simulations on OpenHRP.
- Power law patterns are reproduced (in simulation and experiment).
- Drift correction: better for $\beta = 1/3$ in simulation, the same on the robot.



(a)



(b)

Mixing NMPC walking and Power La

- Increase in β exponent decreases duration.
- The amount of correction is far smaller with $\beta = 1/3$.

β	-1/3	0.0	1/3	2/3
Norm	1.416	0.950	0.642	1.124
Orientation	76.83	89.598	60.453	77.217