33rd Annual Meeting of the Society for Neural Control of Movement, April 2024, Dubrovnik

Using a Stochastic Optimal Control Framework to Model the Control of Complex Human Movement: *Application to an Aerial Acrobatics*

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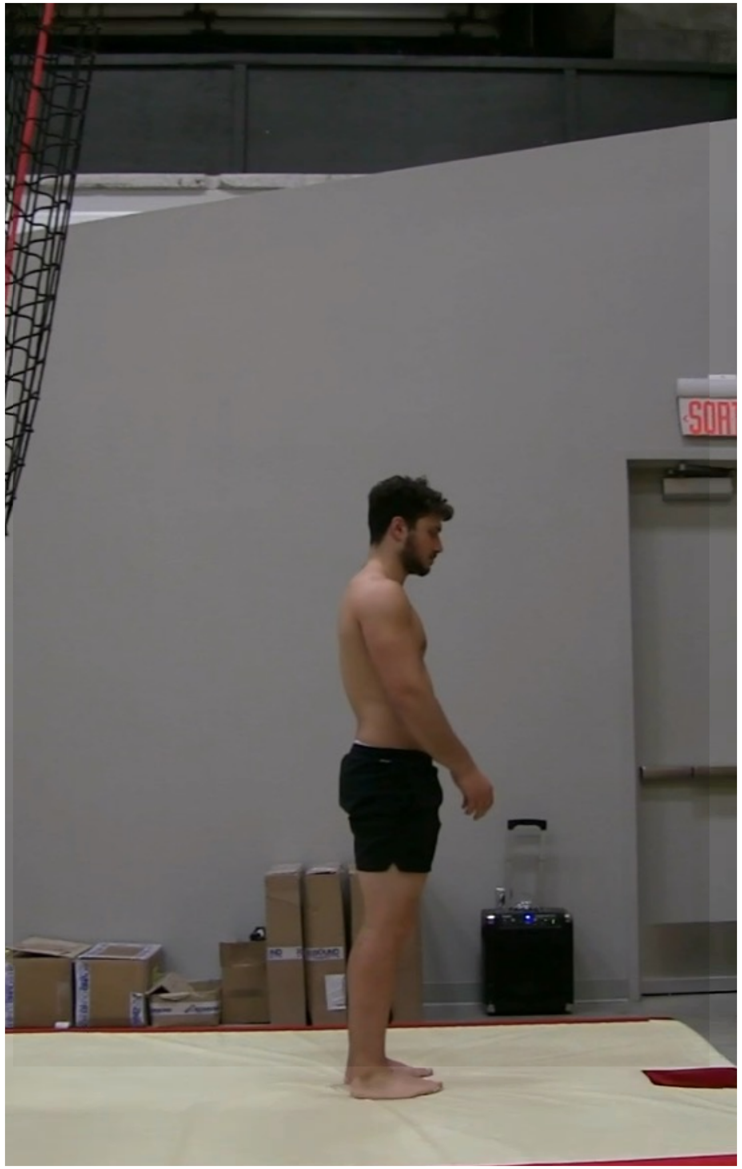
Project context



What is limiting performance?

- Lack of strength
- Lack of power
- Lack of flexibility

} Physical conditioning

- Bad acrobatic technique

} Change of technique

- Poor coordination
- Poor perception of spatial orientation

} Sport-specific exercises

Predictive simulations can answer this question using *"what if"* scenarios

How do athletes choose their strategy?

- Complete the acrobatic
  ↳ Reach landing position
  ↳ Adjust moment of inertia

Task description
+
Skeletal model

- Succeed consistently
  ↳ Motor variability
  ↳ Sensory feedback

Feedback
+
Motor & sensory noise

- Adjust the motor plan
  ↳ Looking at the landing spot
  ↳ Feedforward

Feedforward
+
Vision

Literature

Biomechanics

Optimal Control theory

Chow, C. K., & Jacobson, D. H. (1971)
Ghosh, T. K., & Boykin Jr, W. H. (1976)
Hatze, H. (1976)

Goal: finding optimal motion

Open loop motor command

Complex musculoskeletal models
and
Complex movements

...but are these techniques feasible?

Motor control

Optimal Feedback Control theory

Todorov, E., & Jordan, M. I. (2002)

Goal: finding optimal feedback gains

Closed loop motor control policy
Robust to motor and sensory noises

Simple models

...but is the model representative of the human movement ?

Motor learning

Perception-Action Coordination theory

Gibson, J.J. (1979)

Goal: Determining the role of perception & action in the execution of movements

Closed loop motor control policy where action is perceptually guided and perception is action-oriented

No model

...but how do we predict these sensory-motor strategies?

Optimal Control theory

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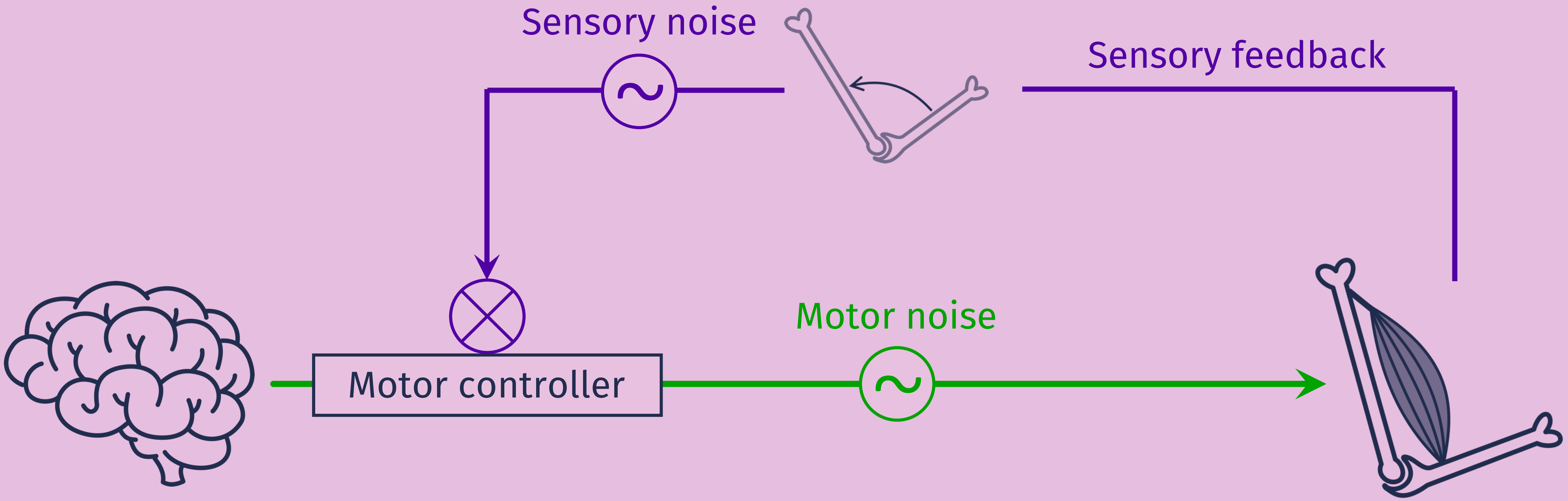

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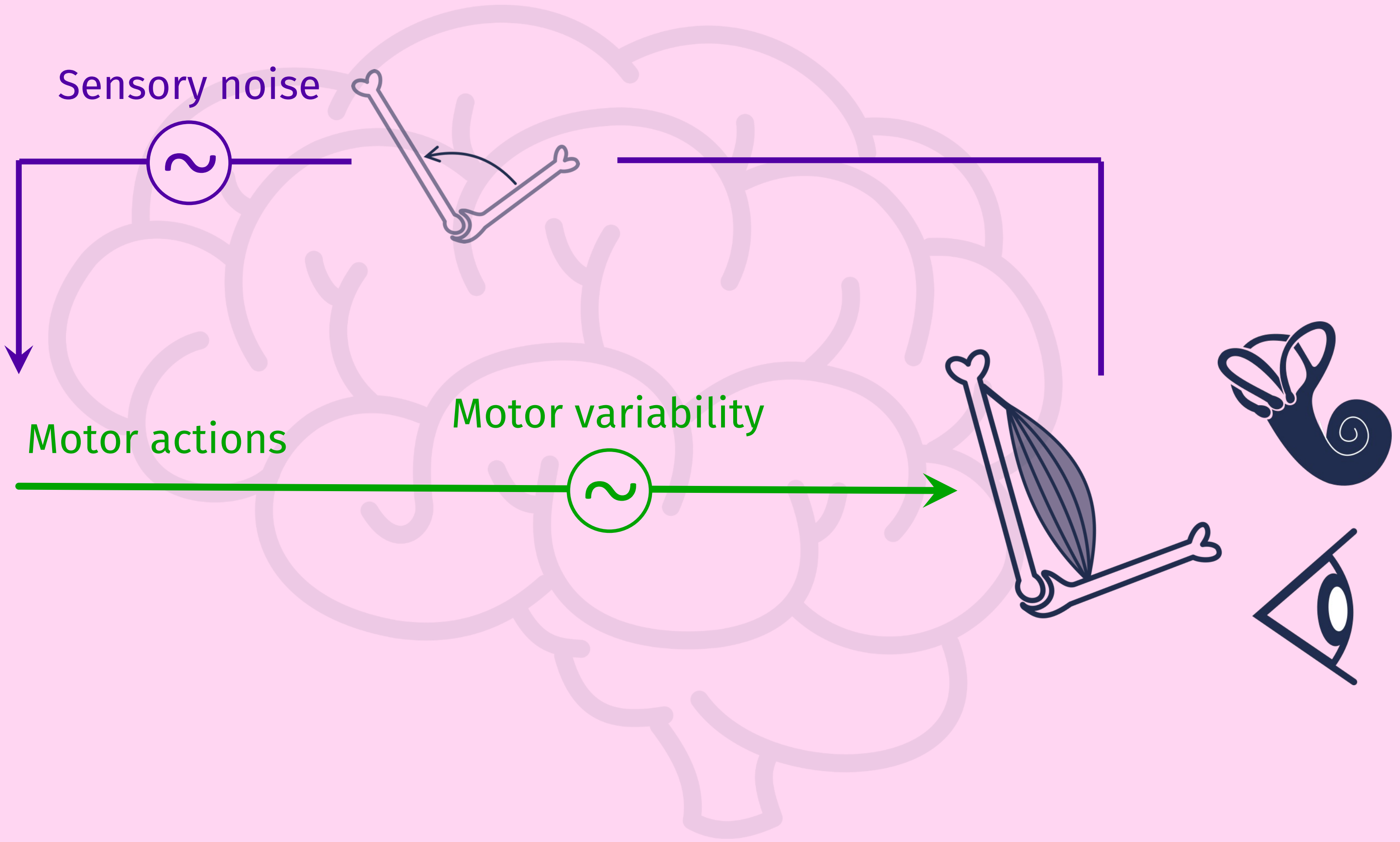
Sensory noise
Motor actions
Motor variability

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Current study

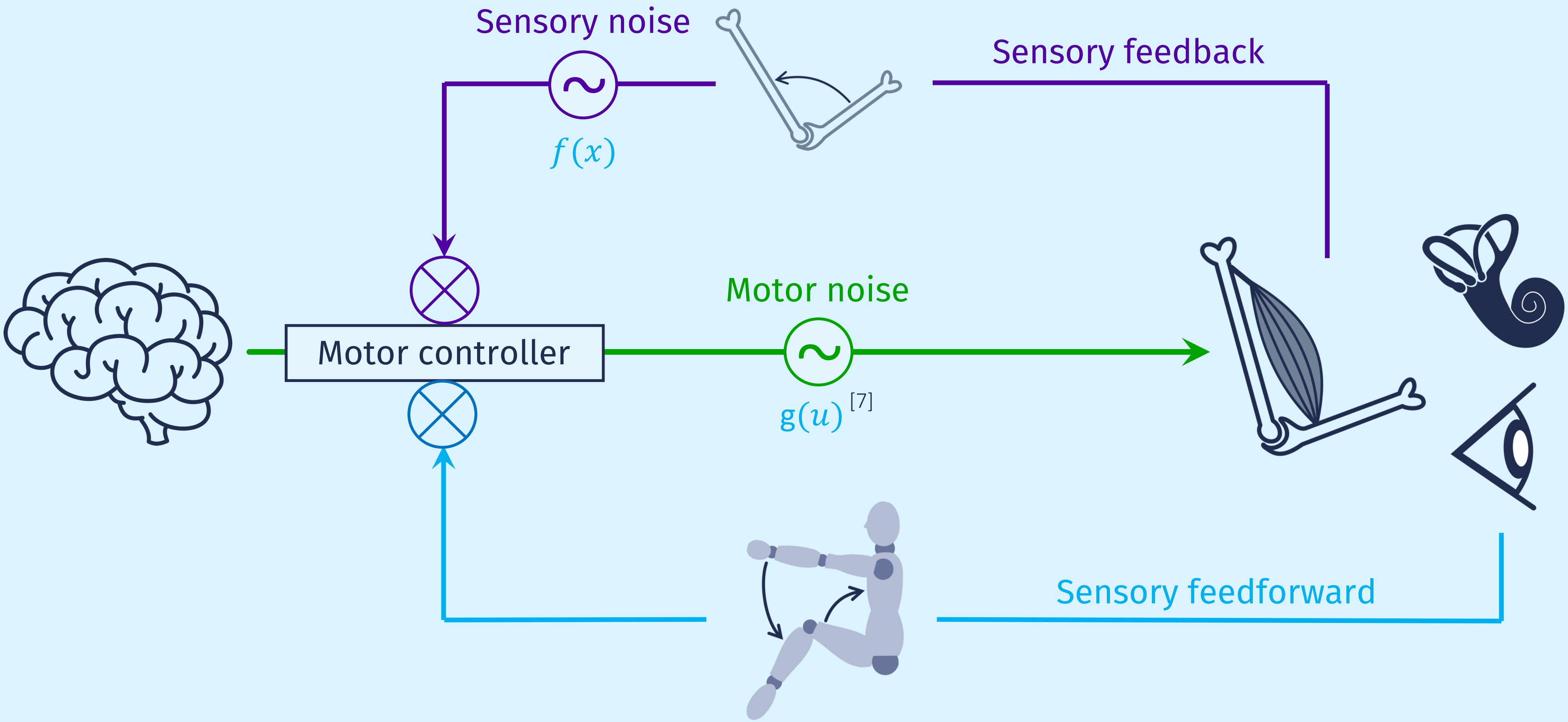
Goal: **Mix these three theories together in a numerical method for stochastic predictive simulations.**

High numerical complexity $\longrightarrow$ computational tricks

Current study

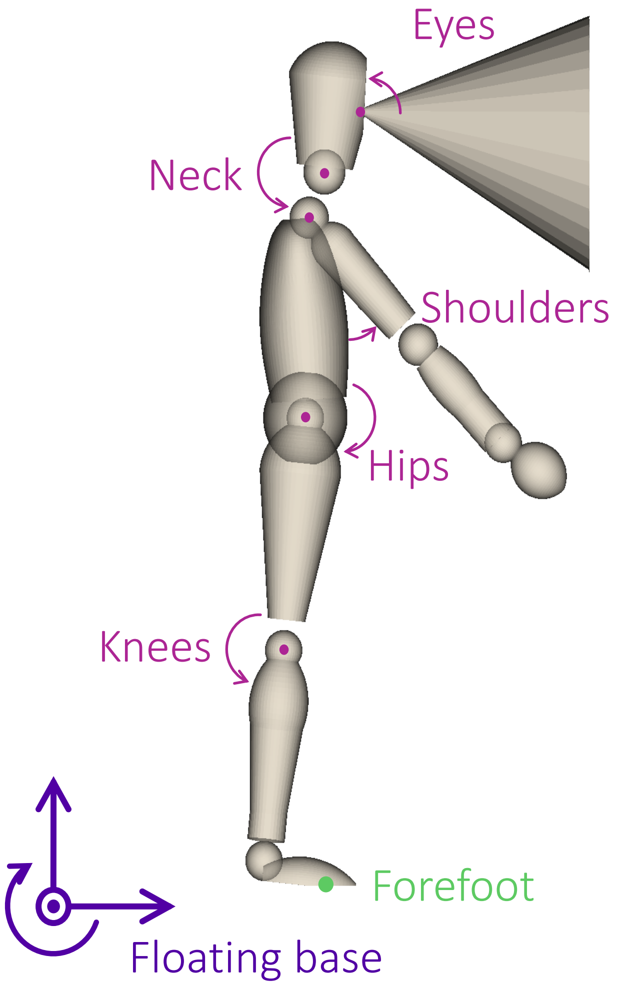
Goal: Mix these three theories together in a numerical method for stochastic predictive simulations.

High numerical complexity ⟶ computational tricks



Harris, C. M., & Wolpert, D. M. (1998).

Methods



8 degrees of freedom (DoF)

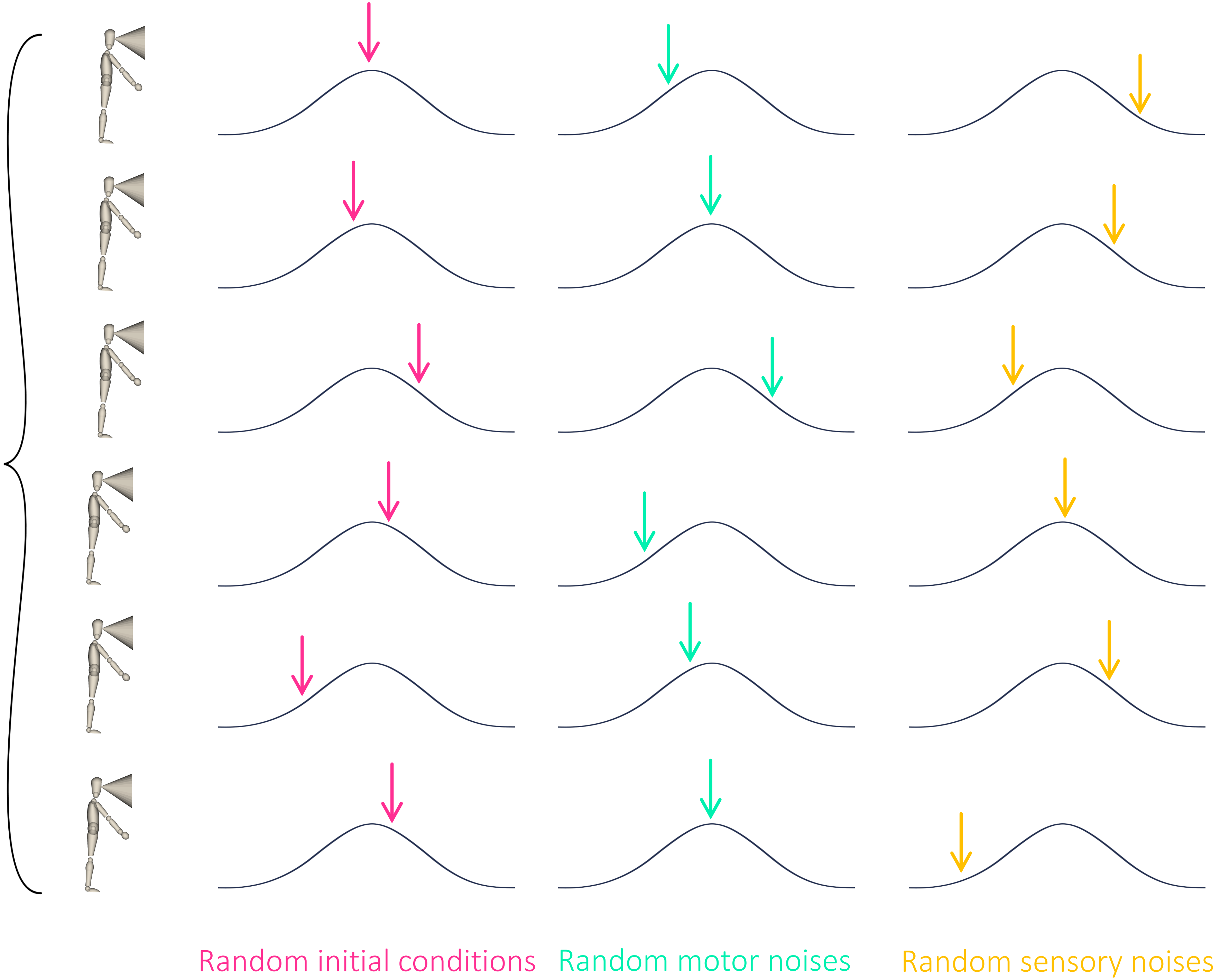
Methods

15 models

Same motor command

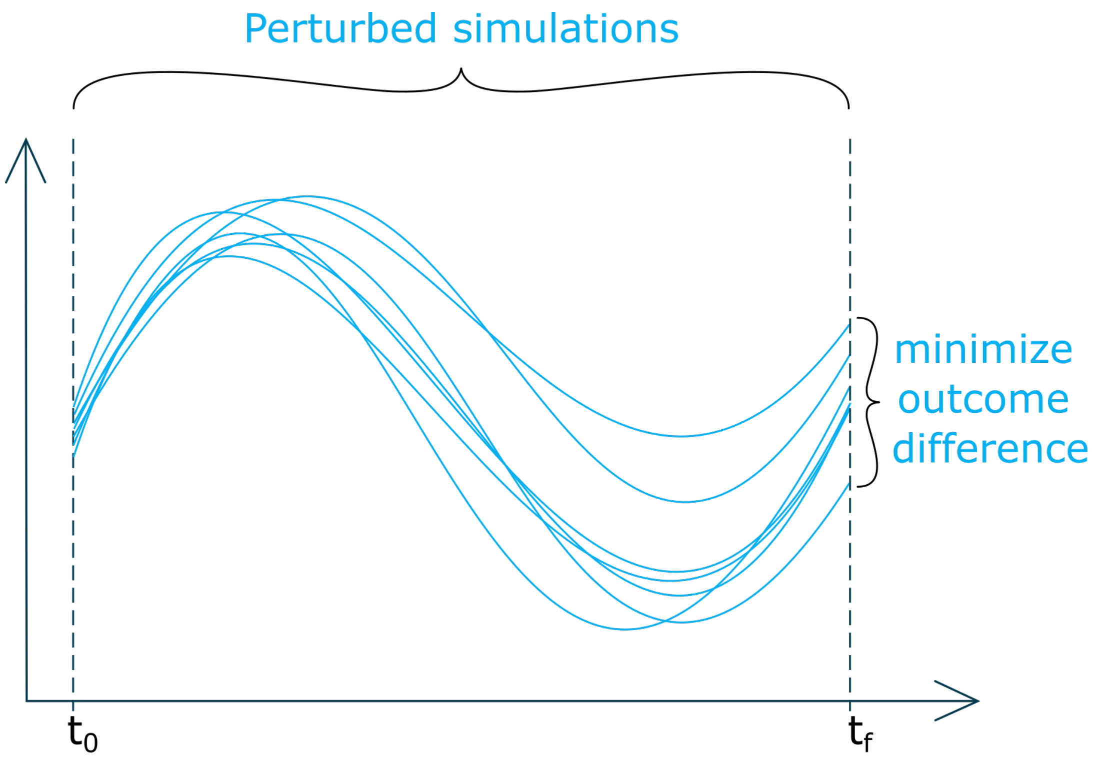
Objective:

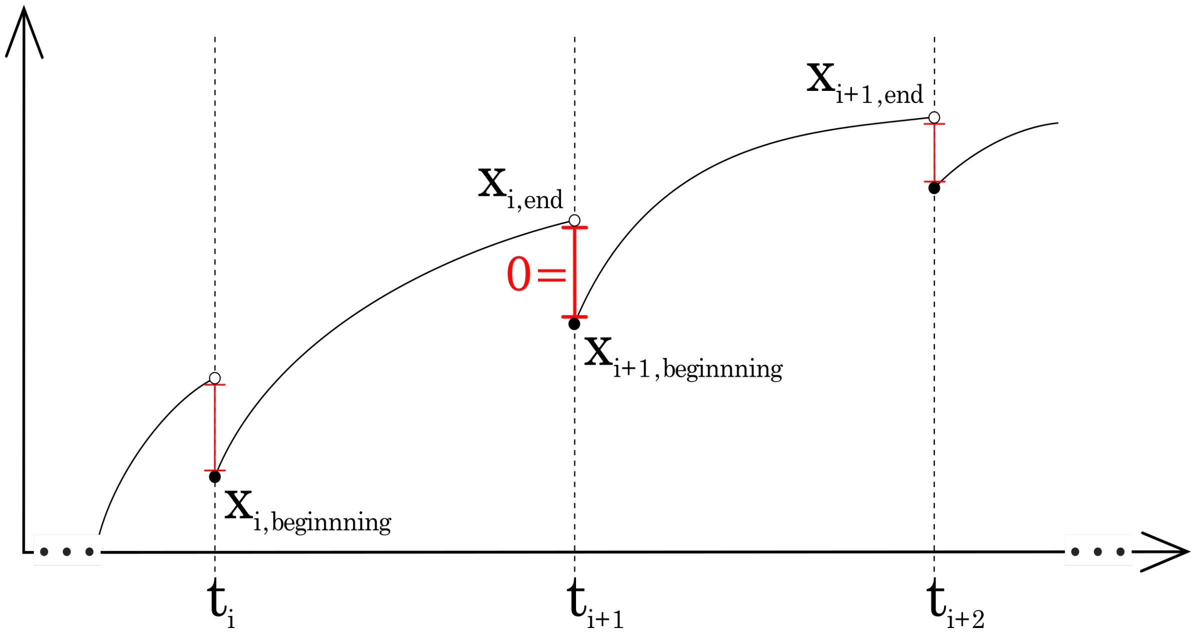
Minimize landing variability between models



Koelewijn, A. D., & van den Bogert, A. J. (2020).

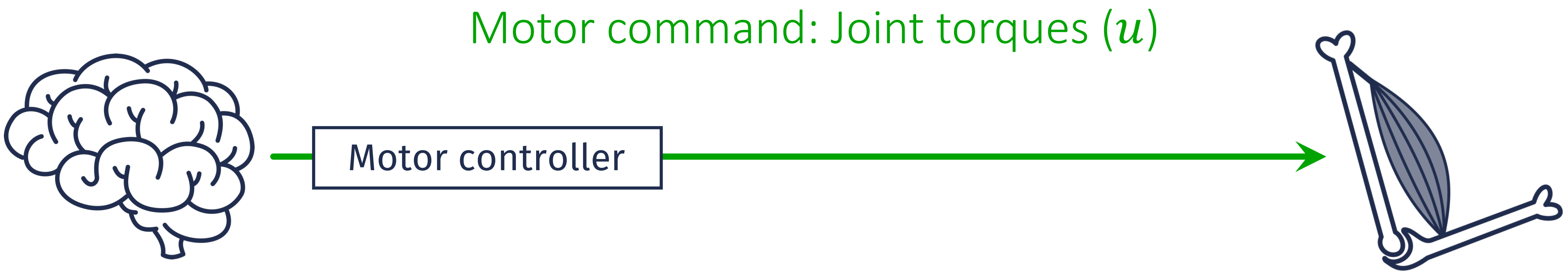
Methods



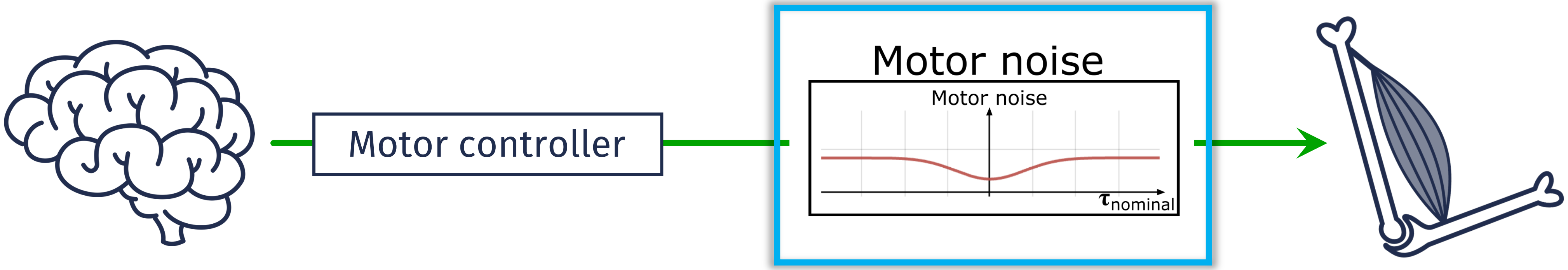


Direct multiple shooting

Methods

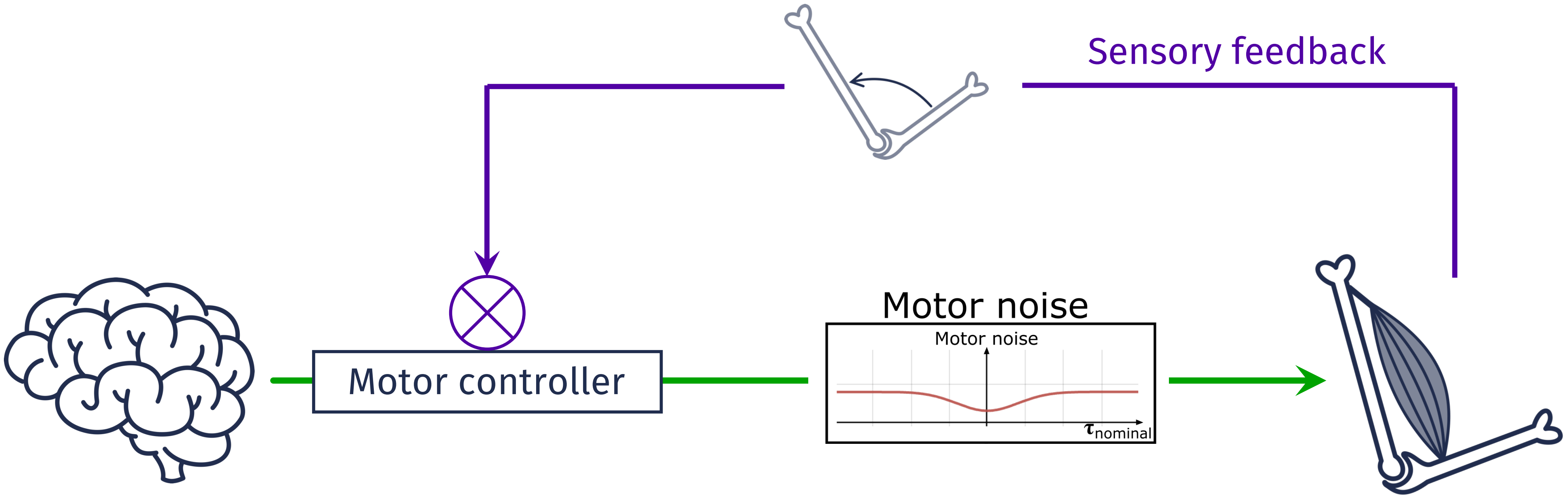


Methods



Methods

Sensory feedback: Joints & head orientation (q, H)
Joints & head velocities $(\dot{q}, \dot{H})$



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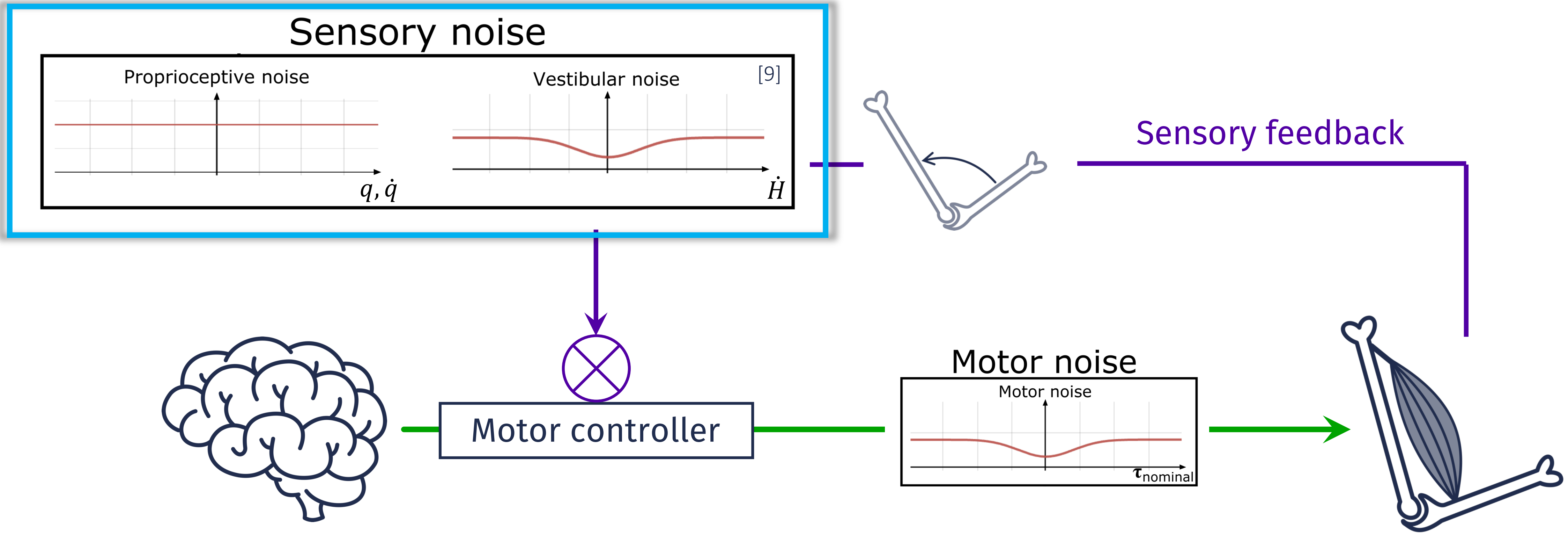
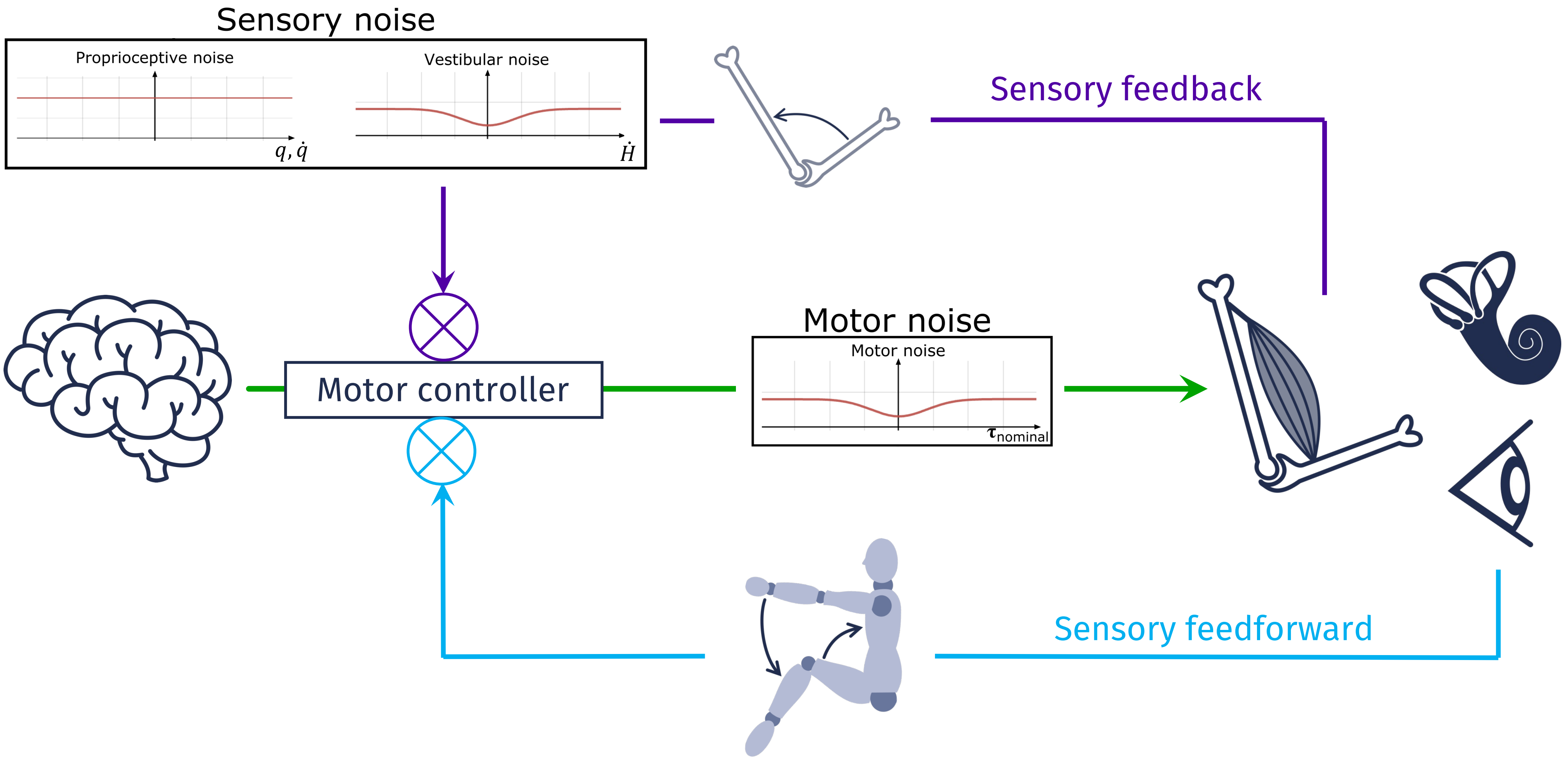
Joints & head velocities $(\dot{q}, \dot{H})$



Kingma, H., & Van de Berg, R. (2016)

Methods

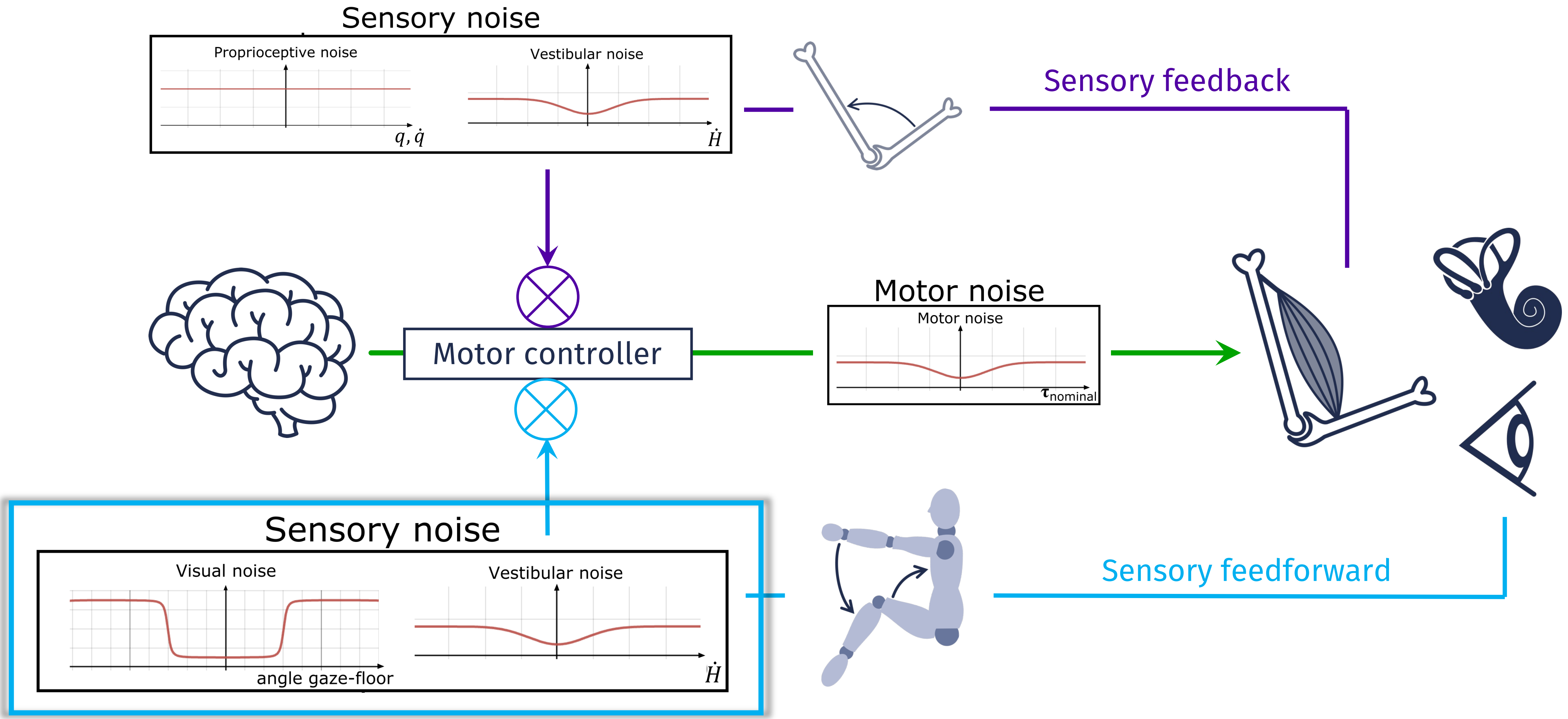
Sensory feedforward: expected somerault at landing ($\theta + \dot{\theta}\Delta t$)[10]



Bardy, B. G., & Laurent, M. (1998).

Methods

Sensory feedforward: expected somersault at landing ($\theta + \dot{\theta}\Delta t$)



Methods

Optimal control
(OCP)

Stochastic optimal control
(SOCP)

Stochastic optimal control
with variable noise and
feedforward
(SOCP+)

Methods

States:
Joint position : $q(t)$
Joint velocities: $\dot{q}(\mathrm{t})$

Controls:
Nominal joint torques: $u(t)$

Optimal control (OCP)

$$\tau_{total} = u + \tau_{passive}$$

Stochastic optimal control (SOCP)

Stochastic optimal control with variable noise and feedforward (SOCP+)

$$\min \quad \tau^2 + \dot{\tau}^2 + T$$

$$s.t. \quad x_{k+1} = F(x_k)$$

Feet on the ground at the end

Center of mass over toes at the end

Methods

States:
Joint position : $q(t)$
Joint velocities: $\dot{q}(t)$

$\underbrace{\qquad\qquad\qquad}_{\text{x 15 models}}$

Controls:
Nominal joint torques: $u(t)$

Others:
Feedback reference: $ref_{fb}(t)$
Feedback gains: $K_{fb}(t)$

Optimal control
(OCP)

Stochastic optimal control
(SOCP)

Stochastic optimal control
with variable noise and
feedforward
(SOCP+)

$$\tau_{total} = u + \tau_{passive}$$
$$+ K_{fb}(ref_{fb} - sensors + w_s) + w_M$$

Somersault rate at landing: $\dot{\theta}(T)$

$$min \quad \tau^2 + \dot{\tau}^2 + T + landing\ variability + K^2 + \dot{K}^2$$

$$s.t. \quad x_{k+1} = F(x_k)$$

$$Feet\ on\ the\ ground\ at\ the\ end$$

$$Center\ of\ mass\ over\ toes\ at\ the\ end$$

$$ref_{fb} = \overline{sensors}$$

Methods

States:
Joint position : $q(t)$
Joint velocities: $\dot{q}(\mathrm{t})$

x 15 models

Controls:
Nominal joint torques: $u(t)$

Others:
Feedback reference: $ref_{fb}(\mathrm{t})$
Feedback gains: $K_{fb}(\mathrm{t})$
Feedforward reference: ref_{ff}
Feedforward gains: $K_{ff}(\mathrm{t})$

Optimal control
(OCP)

Stochastic optimal control
(SOCP)

Stochastic optimal control with variable noise and feedforward
(SOCP+)

$$\tau_{total} = u + \tau_{passive} + K_{fb}(ref_{fb} - sensors + w_s(q,\dot{q})) + w_M(u) + K_{ff}(ref_{ff} - sensors + w_s(q,\dot{q}))$$

$$\min \quad \tau^2 + \dot{\tau}^2 + T + landing\ variability + K^2 + \dot{K}^2$$

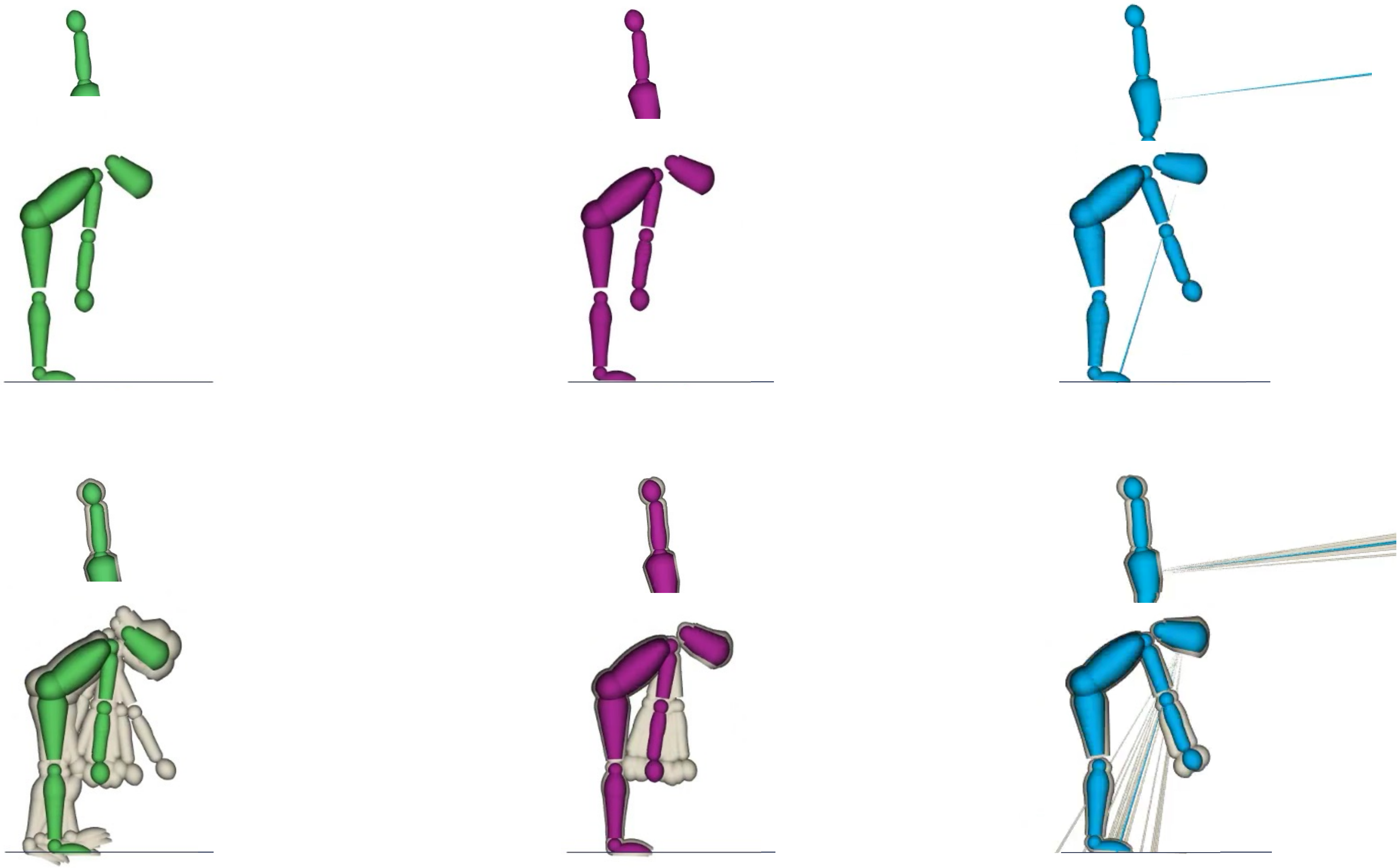
$$s.t. \quad x_{k+1} = F(x_k, \tau_k)$$

$Feet\ on\ the\ ground\ at\ the\ end$

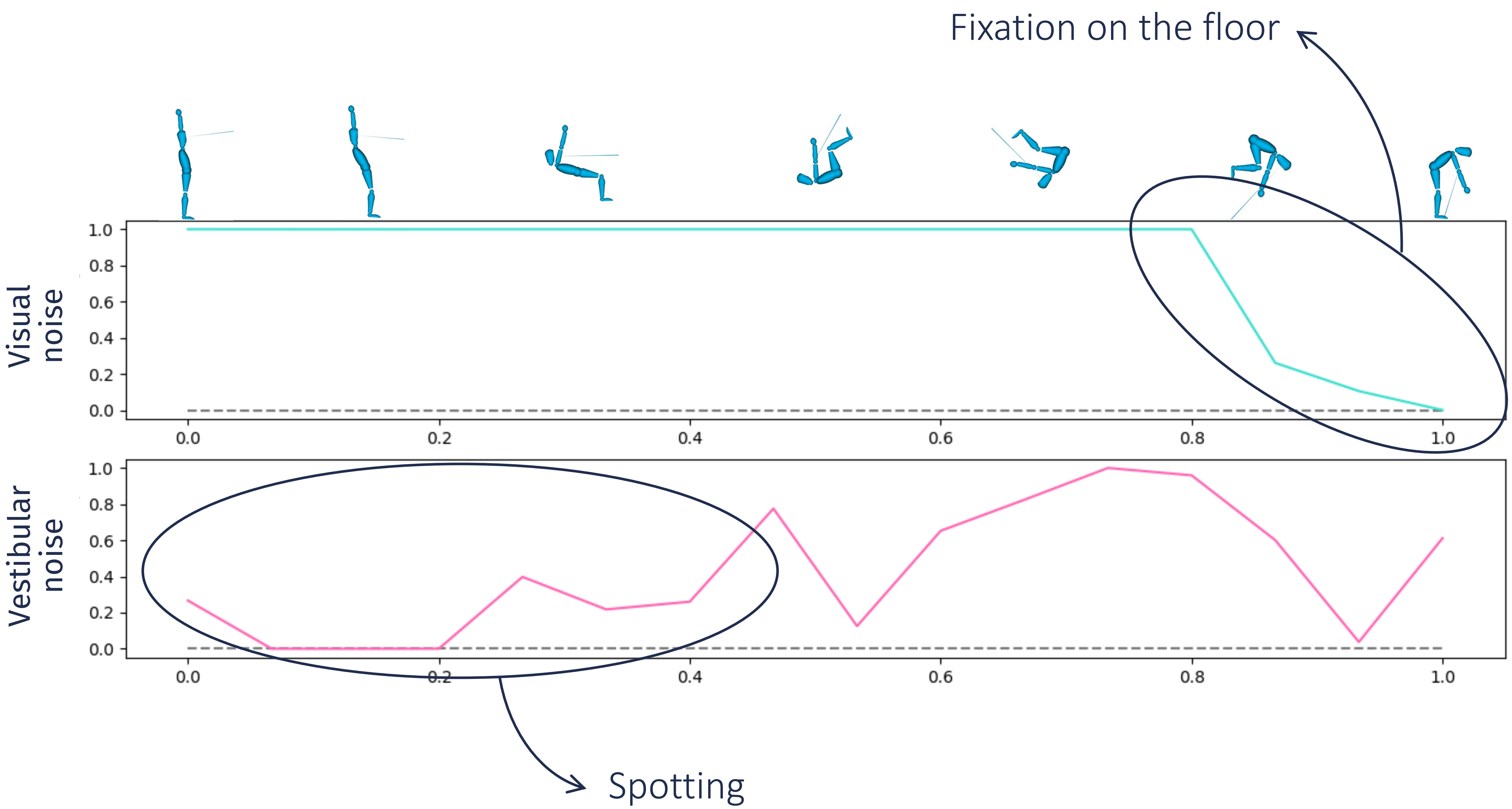
$Center\ of\ mass\ over\ toes\ at\ the\ end$

$$ref_{fb,ff} = \overline{sensors}$$

OCP | SOCP | SOCP+



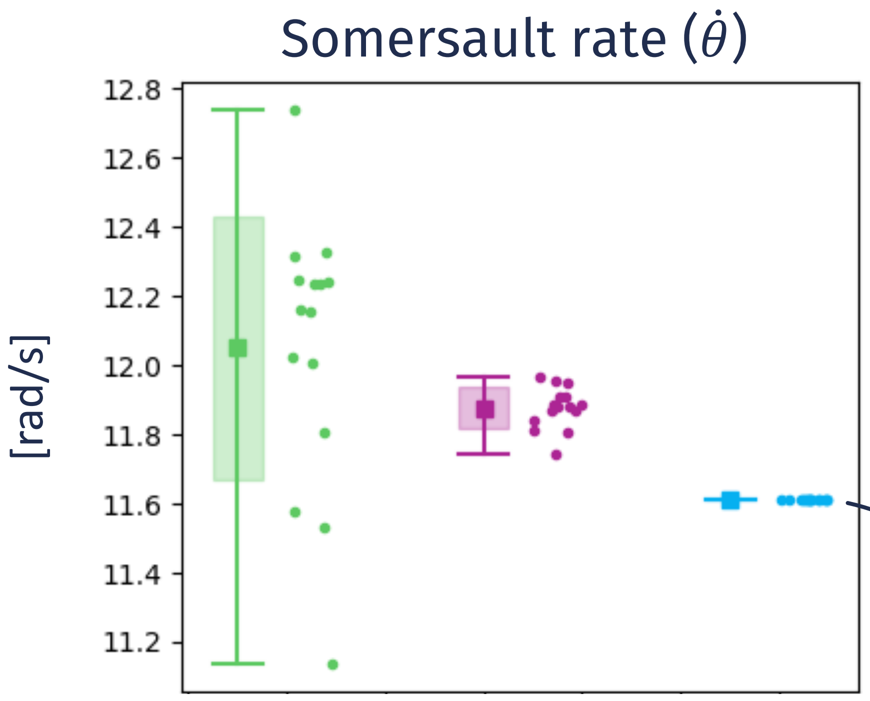
Resolution time: Few seconds | Few days | Few days



Fixation on the floor
Visual noise
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Vestibular noise
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Spotting

Results

Objective: $\tau^2 + \dot{\tau}^2 + T +$ *landing variability* $+ K^2 + \dot{K}^2$

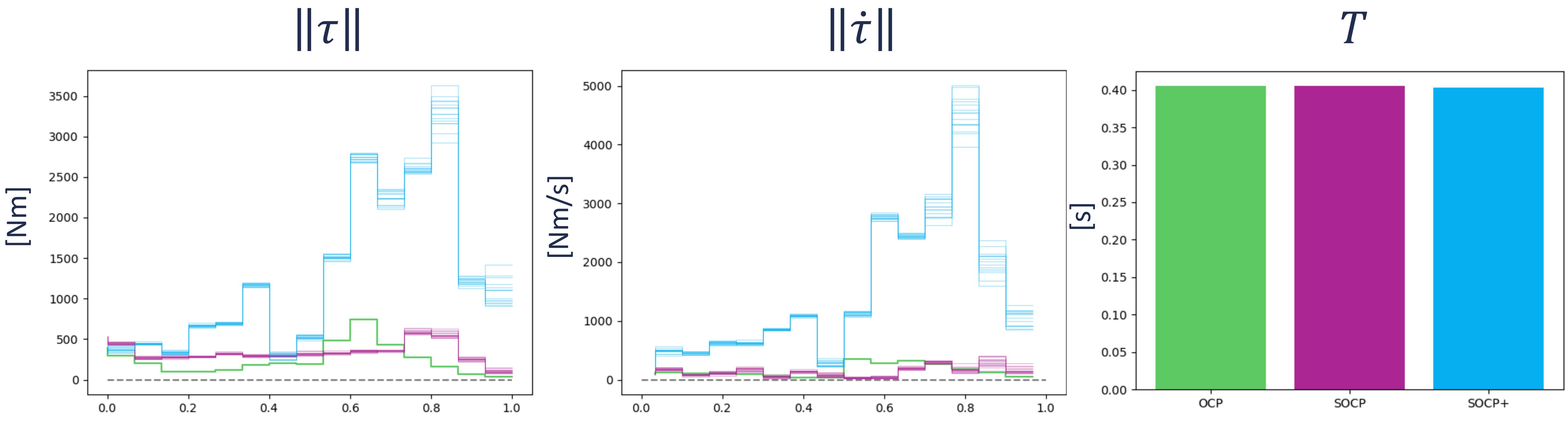


$\theta + \dot{\theta}\Delta t$

— OCP — SOCP — SOCP+

Results

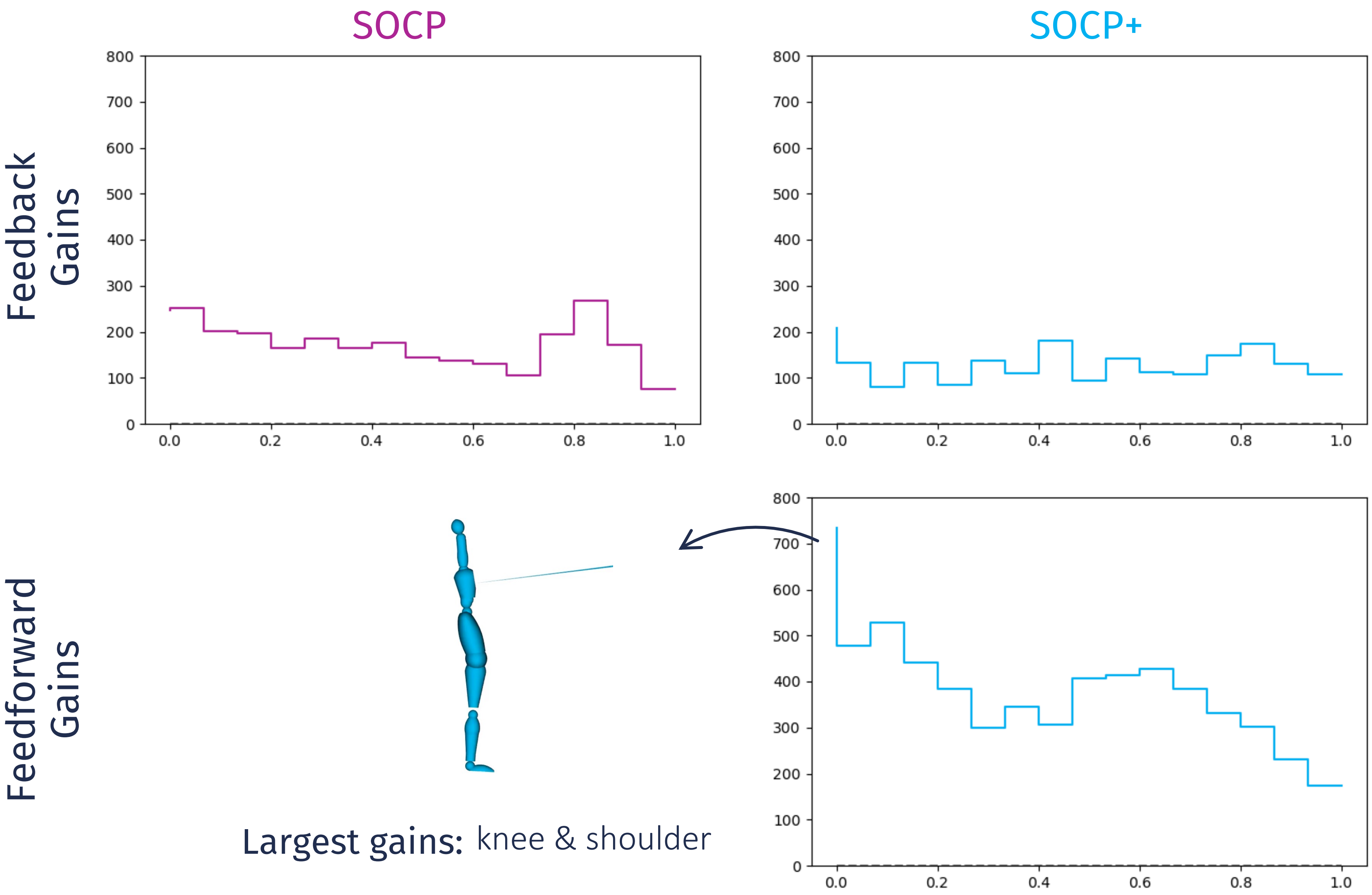
Objective: $\tau^2 + \dot{\tau}^2 + T + landing\ variability + K^2 + \dot{K}^2$



— OCP — SOCP — SOCP+

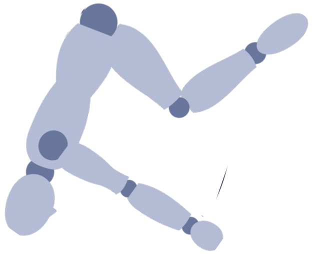
Results

Objective: $\tau^2 + \dot{\tau}^2 + T + landing\ variability + K^2 + \dot{K}^2$



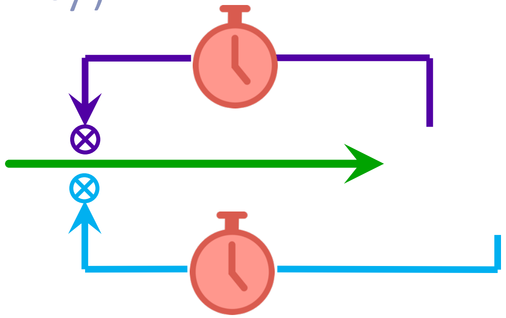
Largest gains: knee & shoulder

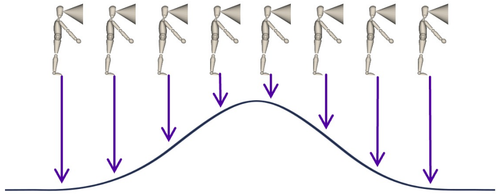
Limitations



Movement simplifications
↳ Only aerial phase (no take-off & landing)
↳ No hand-leg contact (constrained end-effector variability)

Feedback & feedforward delays
↳ Instability?





Sampling instead of considering the distribution
↳ More precise with a larger number of models
↳ Heavy computationally

Expertise is assumed (perception-action)
↳ Idealized motor command
↳ Task-specific gains

Take home message

- Confirmation of the relevance of this **numerical method**
- The use of stochastic optimal control can increase the **robustness** of control policies
- The addition of **feedforward** term and **variable noise** can increase the realism of control policies
- There is still room for **realism** improvements, but still a promising start!

References

[1] Chow, C. K., & Jacobson, D. H. (1971). Studies of human locomotion via optimal programming. Mathematical Biosciences, 10(3-4), 239-306.

[2] Ghosh, T. K., & Boykin Jr, W. H. (1976). Analytic determination of an optimal human motion. Journal of Optimization Theory and Applications, 19(2), 327-346.

[3] Hatze, H. (1976). The complete optimization of a human motion. Mathematical Biosciences, 28(1-2), 99-135.

[4] Todorov, E., & Jordan, M. I. (2002). Optimal feedback control as a theory of motor coordination. Nature neuroscience, 5(11), 1226-1235.

[5] Gibson, J. J. (1979). The ecological approach to visual perception. Houghton, Mifflin and Company.

[6] Van Wouwe, T., Ting, L. H., & De Groote, F. (2022). An approximate stochastic optimal control framework to simulate nonlinear neuro-musculoskeletal models in the presence of noise. PLOS Computational Biology, 18(6), e1009338.

[7] Harris, C. M., & Wolpert, D. M. (1998). Signal-dependent noise determines motor planning. Nature, 394(6695), 780-784.

[8] Koelewijn, A. D., & van den Bogert, A. J. (2020). A solution method for predictive simulations in a stochastic environment. Journal of biomechanics, 104, 109759.

[9] Kingma, H., & Van de Berg, R. (2016). Anatomy, physiology, and physics of the peripheral vestibular system. Handbook of clinical neurology, 137, 1-16.

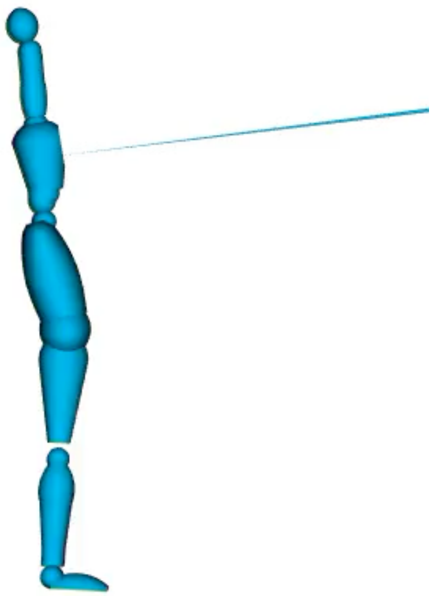
[10] Bardy, B. G., & Laurent, M. (1998). How is body orientation controlled during somersaulting?. Journal of Experimental Psychology: Human Perception and Performance, 24(3), 963.

Questions ?

Open source code:

EveCharbie/Stochastic_standingBack

Bioptim
Biomechanical optimal control



S2M
Simulation et Modélisation du Mouvement

Université de Montréal

Own the Podium | À nous le podium

Mitacs

CRSNG NSERC

Foncer/Create OPSIDIAN

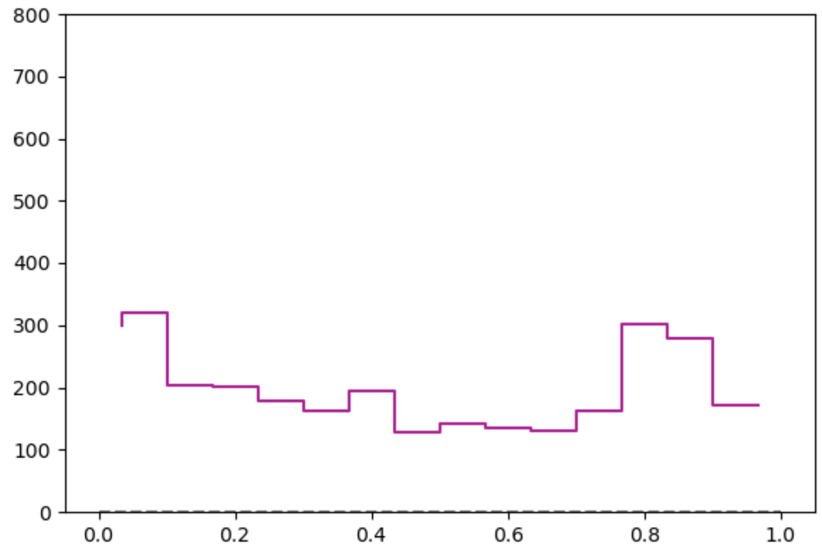
Results

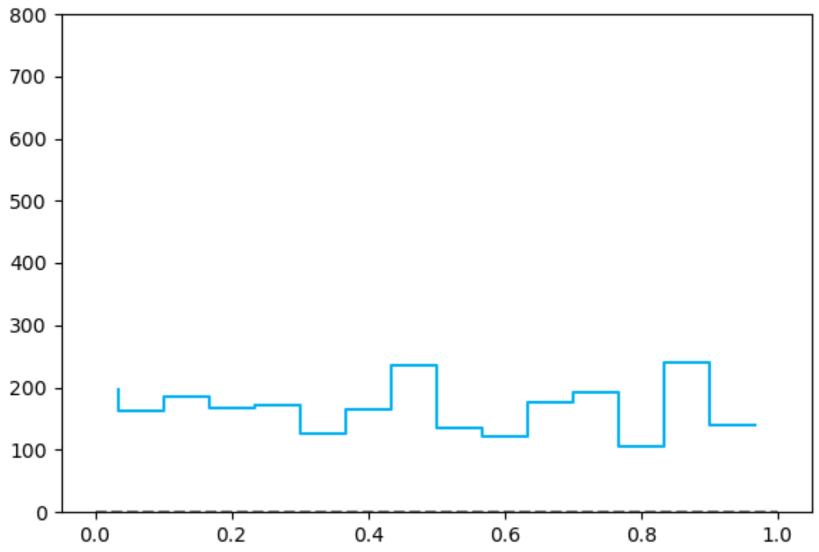
Objective: $\tau^2 + \Delta\tau^2 + T + landing\ variability + K^2 + \Delta K^2$

SOCP

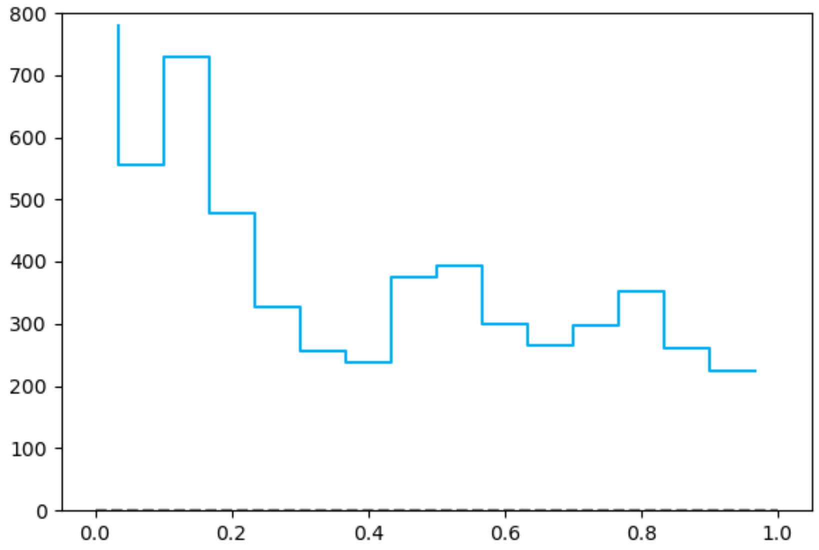
SOCP+

Feedback Gains





Feedforward Gains



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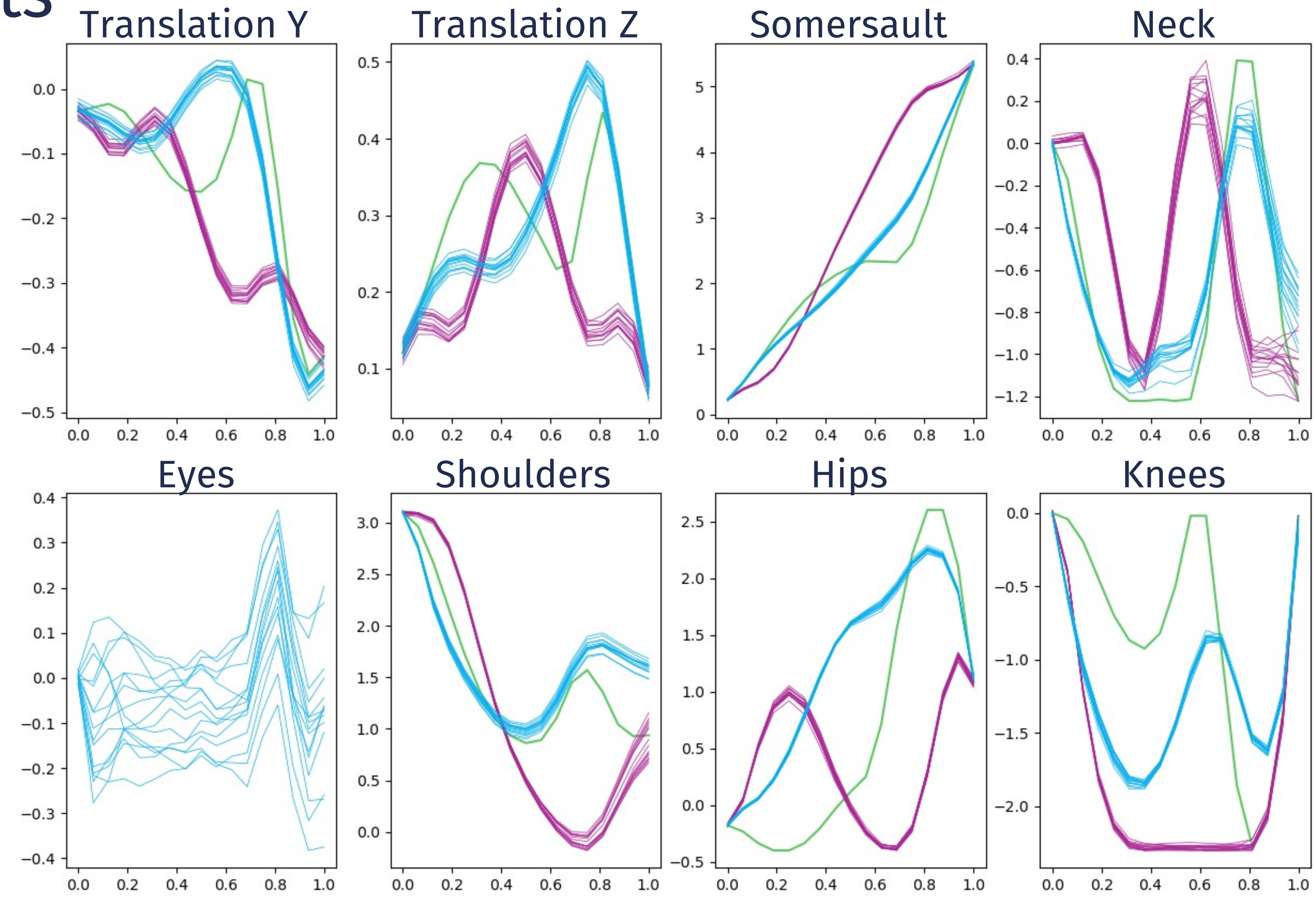


Translation Y
Translation Z
Somersault
Neck
Eyes
Shoulders
Hips
Knees

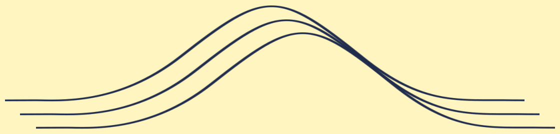
Van Wouwe, T., Ting, L. H., & De Groote, F. (2022)

Complex musculoskeletal model

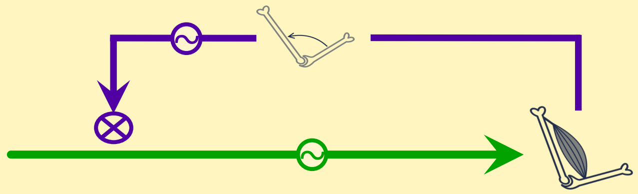
- 6 muscles
- 2 joints

Robust control strategy

- Propioceptive feedbacks
- Motor & sensory noises

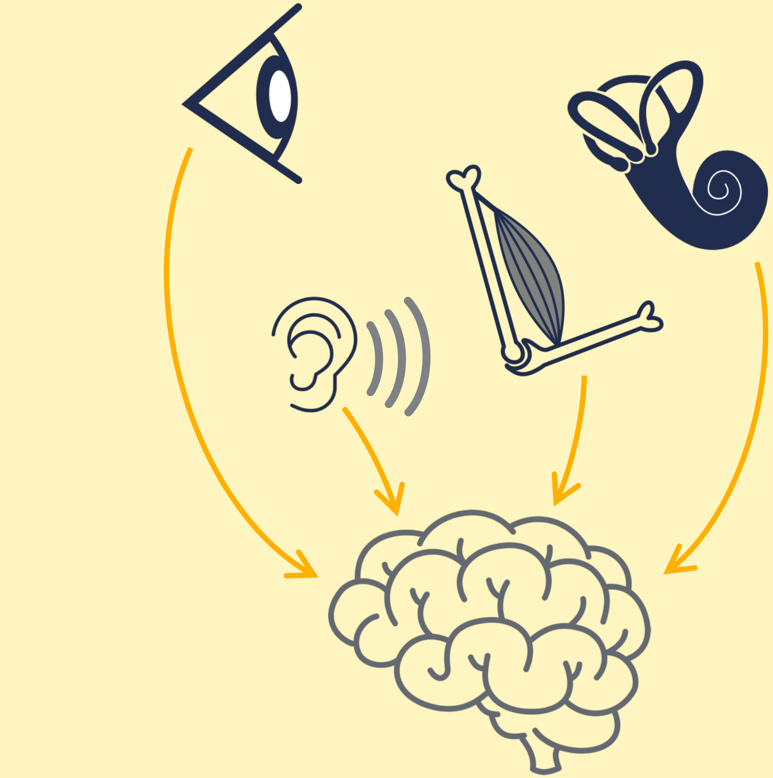


State distribution



Simple pointing task

- Only one feedback
- Only two joints
- No perception-action interaction



- 16+1 nodes

- Motor noise STD: 0.5
- Position proprioception noise STD: 0.005
- Velocity proprioception STD: 0.015
- Vestibular and visual noise STD: 0.015

$$\tau_{total} = u + \tau_{passive} + K_{fb}(ref_{fb} - sensors + w_s(q,\dot{q})) + w_M(u) + K_{ff}(ref_{ff} - sensors + w_s(q,\dot{q}))$$

$$\ddot{q}_k = M(q_k)^{-1}(\tau_k - N(q_k, \dot{q}_k) - G(q_k))$$

M = mass matrix
N = non-linear effects (Coriolis and centrifugal effect)
G = gravity effects

$[q_{k+1}, \dot{q}_{k+1}]$ are obtained by integrating with 5 steps of a 4th order Runge-Kutta