Motor Learning Methods for Humanoid Control

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Outline

- Efficiently using collected data.
- Learning from demonstration.
- Hierarchical learning architecture.

Efficiently using collected data

Using Previous Experiences as Simulation Models

[Sugimoto, Sugiyama, Morimoto et al., IEEE Robot. Automat. Mag., 2016]

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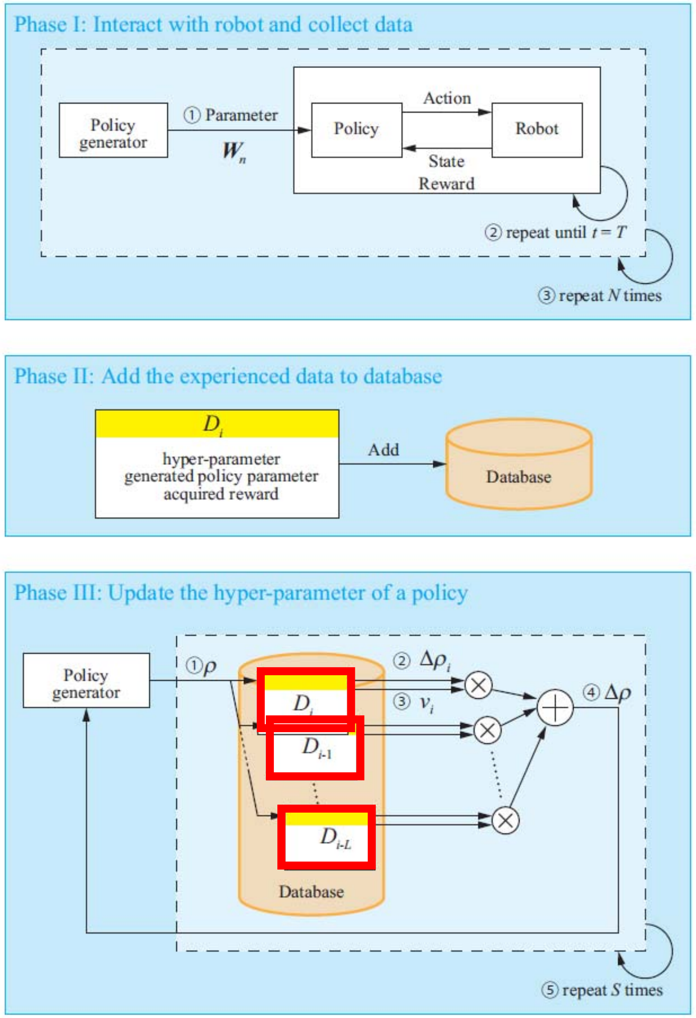

Phase 1: Collect data from real environment using policy stochastically generated with policy generator (hyper-parameter).

Phase 2: Add collected data to database.

Phase 3: Update policy's hyper-parameter using stored data as simulation models.

Basketball shooting task

Basketball-shooting Task

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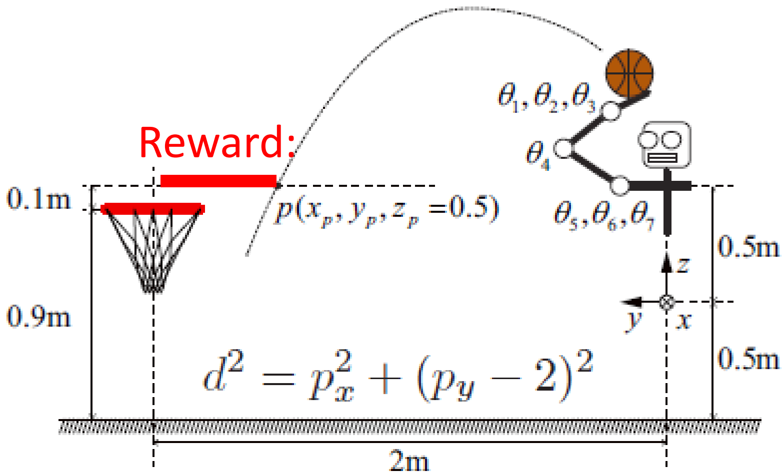

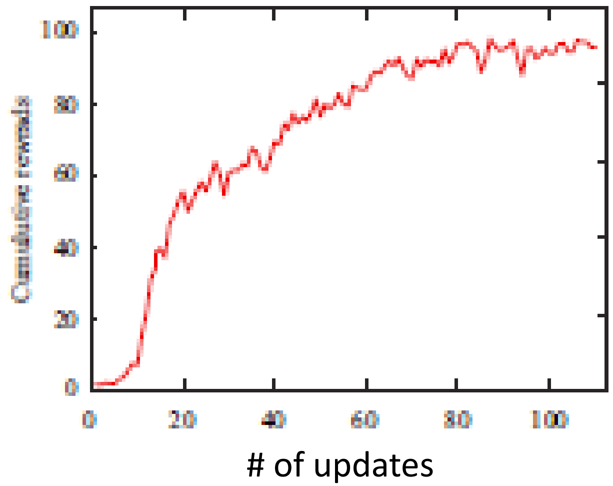

[Sugimoto, Sugiyama, Morimoto et al., IEEE Robot. Automat. Mag., 2016]

Policy model: $\underbrace{\mathbf{u}(t)}_{\text{Desired joint angle}} = \underbrace{\mathbf{w}}_{\text{Policy parameter}}{}^T \phi(t)$

Policy generator: $p(\mathbf{w} \mid \underbrace{\rho}_{\text{Hyper parameter}})$

Gradient was estimated based on IW-PGPE. [T. Zhao, M. Sugiyama et al., Neural Computation, 2013]

Result

[Sugimoto, Sugiyama, Morimoto et al.,
IEEE Robot. Automat. Mag., 2016]

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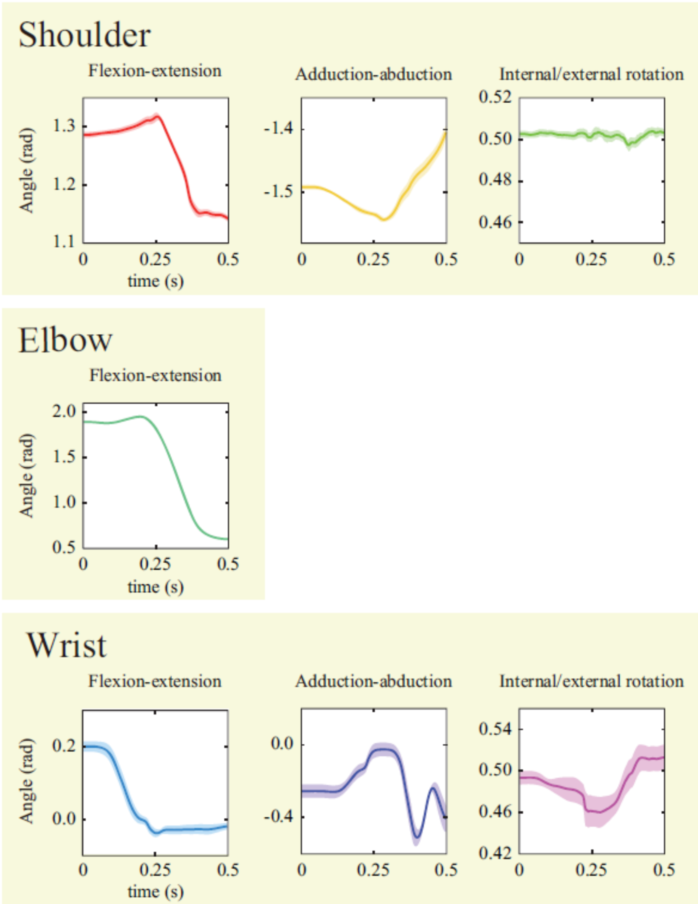
Acquired Basket-ball Shooting Joint Trajectories



Learning from demonstration

Learning from Demonstration

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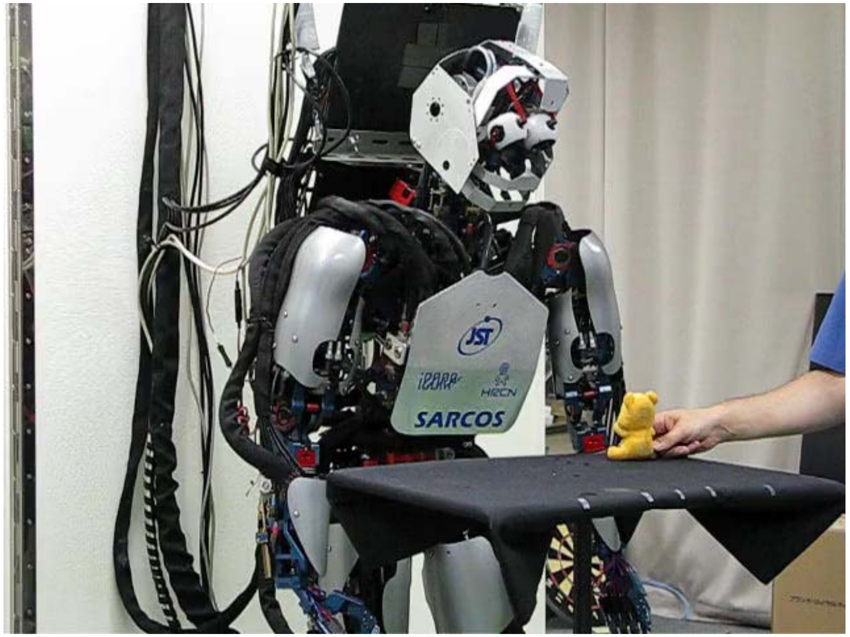
[Ude, Morimoto et al., IEEE Trans. on Robotics, 2010]



Learning from Demonstration

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Dynamic Movement Primitives

[Ijspeert et al., 2002]

[Ude, Morimoto et al., IEEE Trans. on Robotics, 2010]

Point attractor dynamics:

$$\tau \dot{z} = \alpha_z (\beta_z (g - y) - z) + \boxed{f(x)}$$

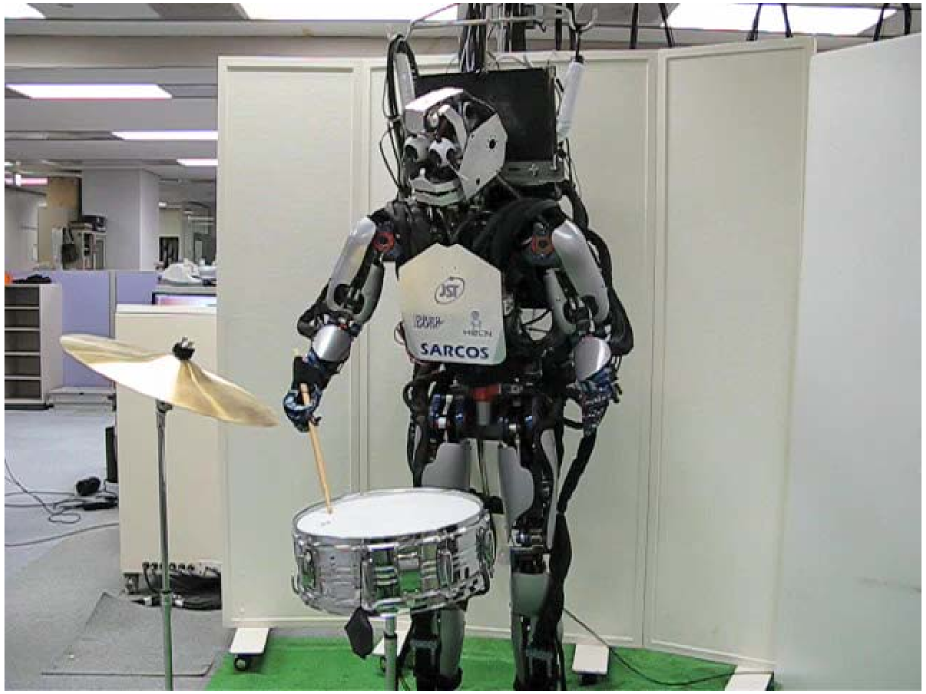
$$\tau \dot{y} = z$$

Phase-dependent modulation input:

$$\boxed{f(x)} = \frac{\sum_{i=1}^{N} w_i \Psi_i(x)}{\sum_{i=1}^{N} \Psi_i(x)} x, \ \Psi_i(x) = \exp\left(-h_i (x - c_i)^2\right)$$

Phase:

$$\tau \dot{x} = -\alpha_x x$$



Hierarchical Reinforcement Learning: Application to Stand-up Movements

[Morimoto and Doya, 2001]

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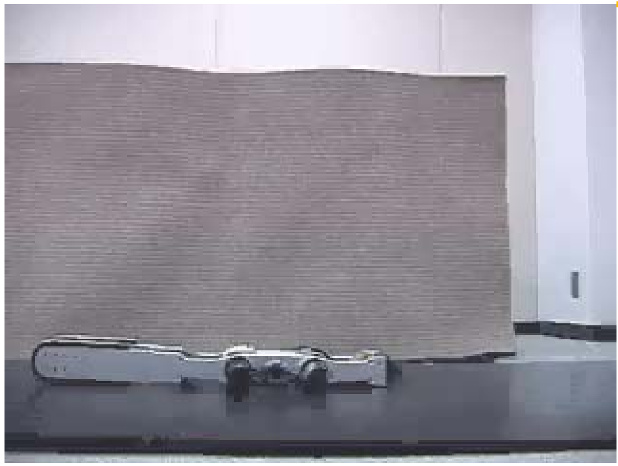
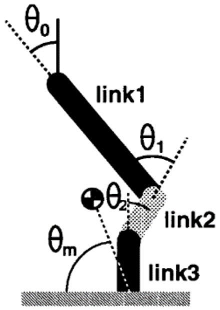
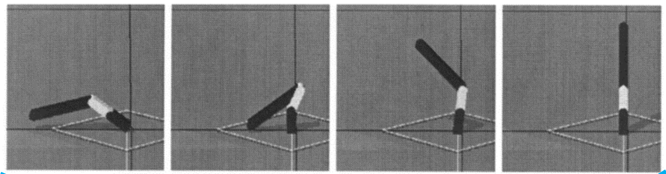
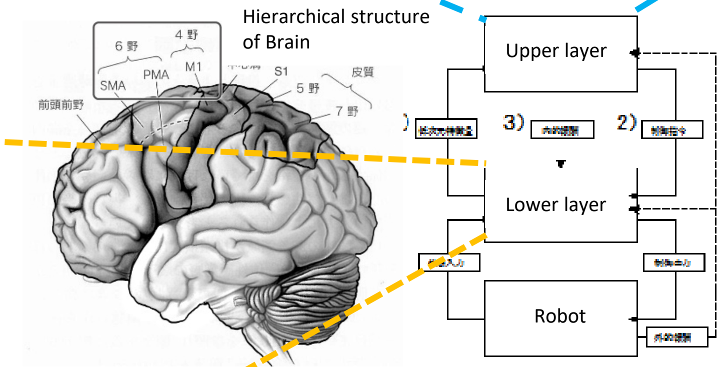
Learning trials

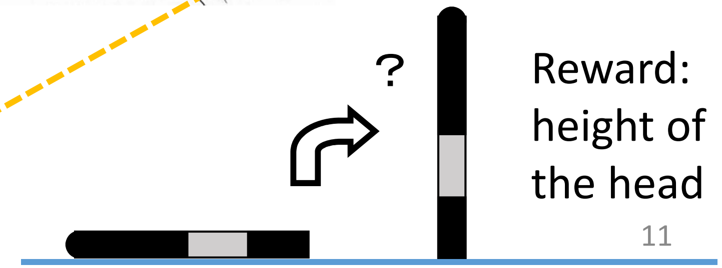
After learning trials











Reward: height of the head

Hierarchical learning architecture

Model Predictive Control (MPC)

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- Online derivation of the optimal control trajectory at each time step, using the first control output.

- Although each optimal control trajectory provides feedforward controller, MPC effectively works as *feedback* control policy due to the optimal control trajectory calculation at each time step.

State
$\boldsymbol{x}_k$

$$\min_{\boxed{\boldsymbol{u}_k}, \cdots, \boldsymbol{u}_{N+k-1}} J_k = \sum_{i=k}^{N+k-1} \underbrace{r(\boldsymbol{x}_i, \boldsymbol{u}_i)}_{\text{Immediate cost}} + \underbrace{\Phi(\boldsymbol{x}_{N+k})}_{\text{Terminal cost}}$$

Optimized
control input
$\boxed{\boldsymbol{u}_k^*}$

MPC Can be Used to Generate Variety of Motions

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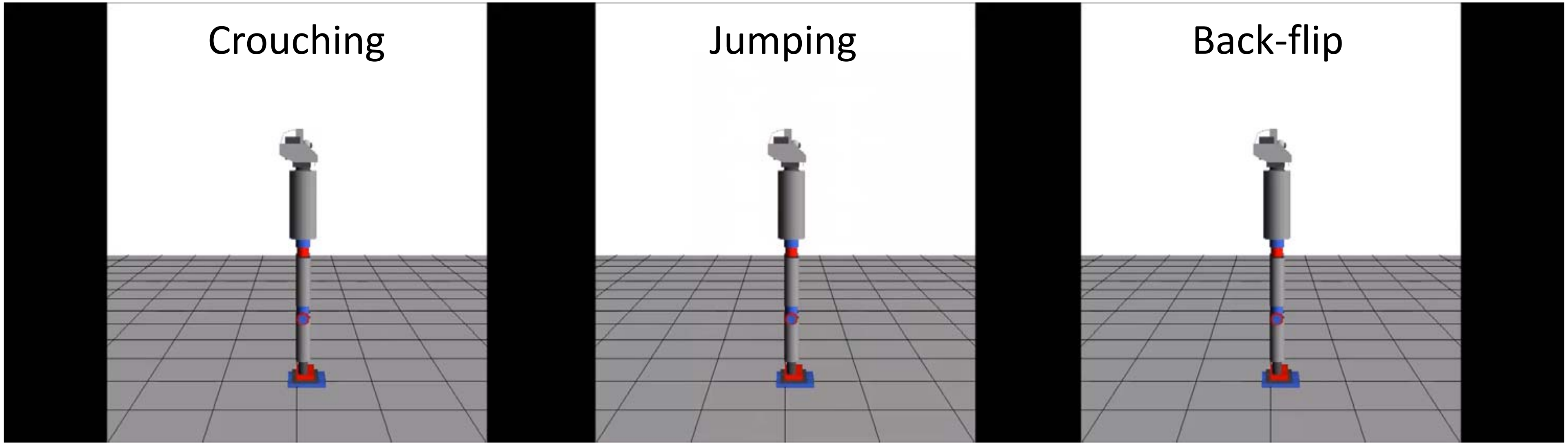
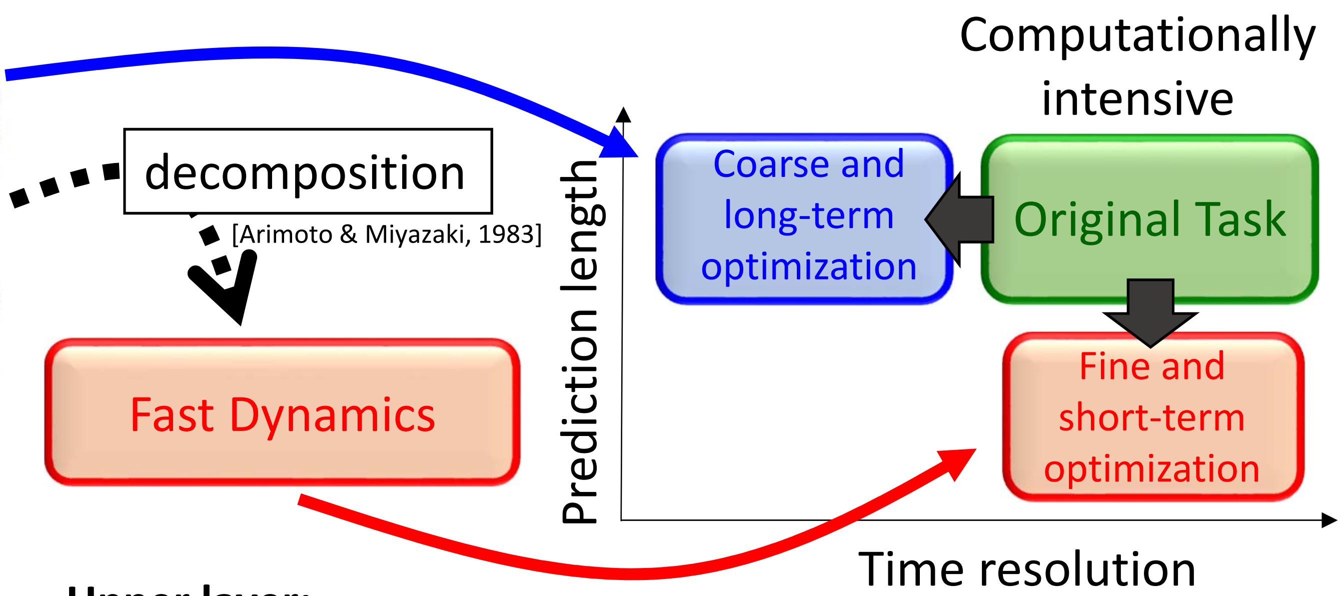


- Optimal control trajectories derived at each time step: MPC is computationally intensive and not applicable to real-time/many-DoF robot control (e.g. humanoids) to generate fast and dynamic movements.

Hierarchical MPC Strategy with Singular Perturbed System

[Ishihara and Morimoto, Humanoids, 2015]



Upper layer:

- Longer time horizon with larger time step in MPC framework.
- Derive movement trajectory that involves longer-term effect but coarse planning in terms of control frequency.

Lower layer:

- Shorter time horizon with smaller time step in MPC framework.
- Derive movement trajectory that involves shorter-term effect but fine planning in terms of control frequency.

Toward Agile Movement Like Human Experts

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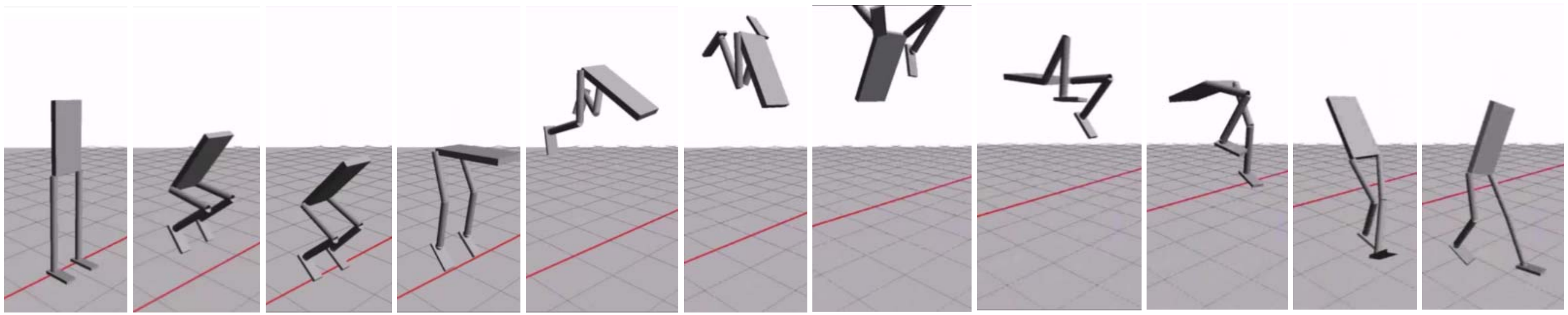
Generated front flip movement by using the proposed method:



Discussion:
Stable Interactions between Different Learning Systems

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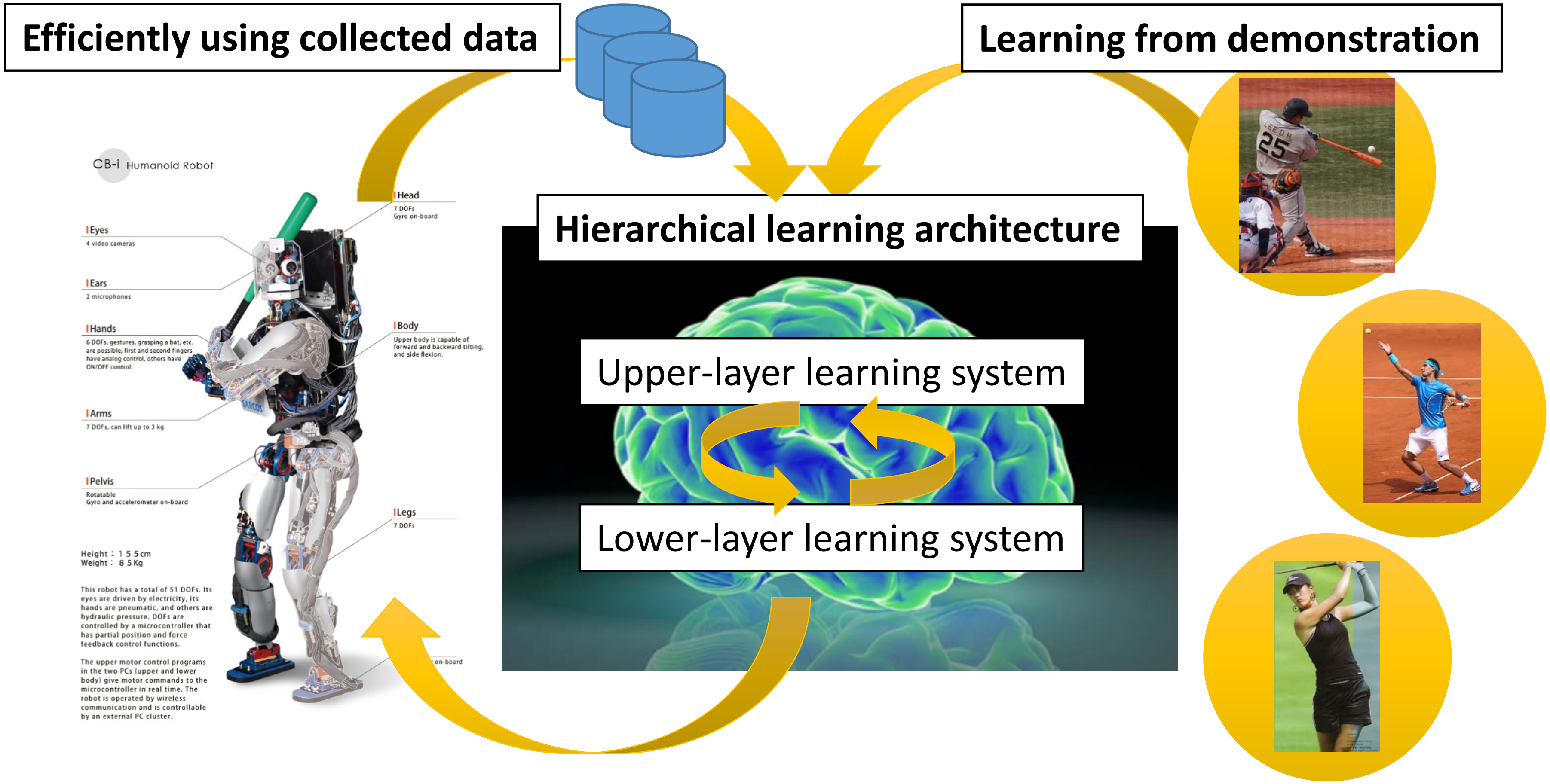

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