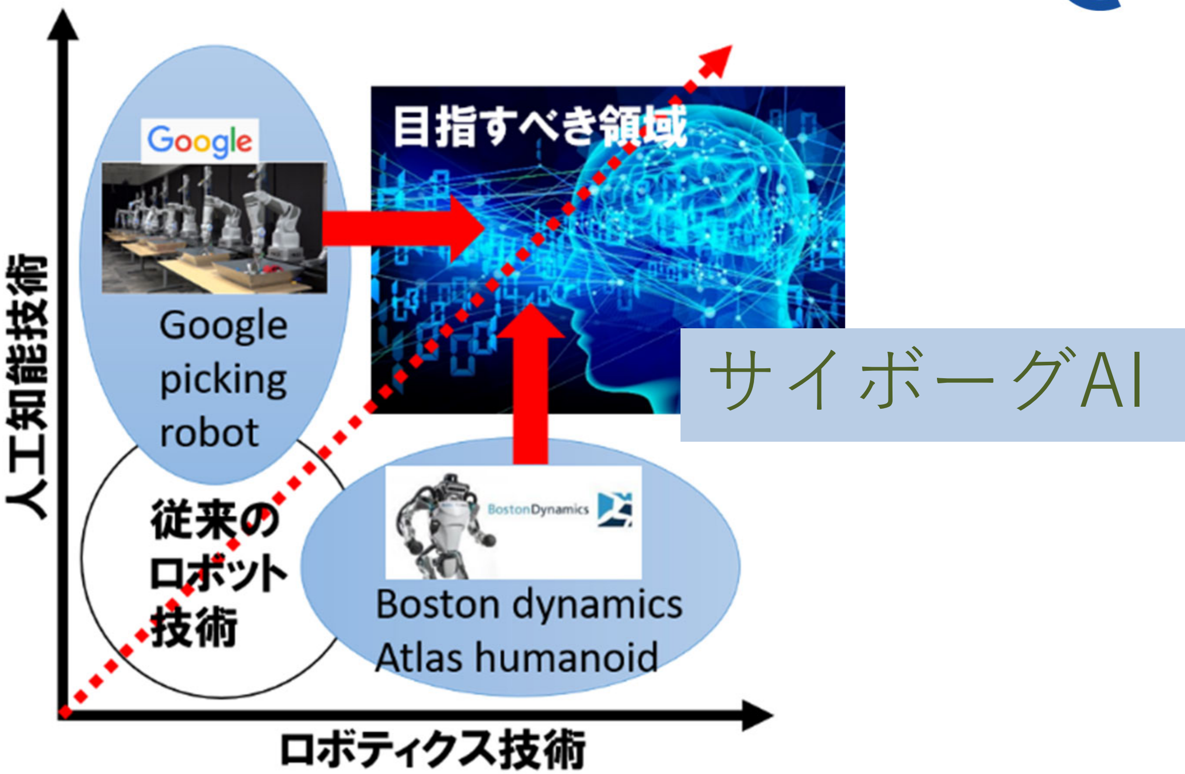
サイボーグAIの研究開発

ATR 脳情報通信総合研究所
森本　淳

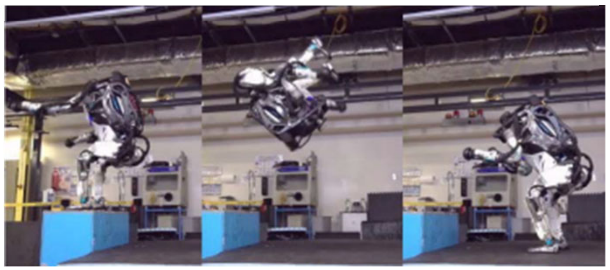
サイボーグAIの目指す領域

- 深層学習で画像から物体を認識、90%の成功率で把持
- 必要なデータ数、試行回数において人間に大きく劣る

Levine, S., Pastor, P., Krizhevsky, A., & Quillen, D. (2016, 2018).



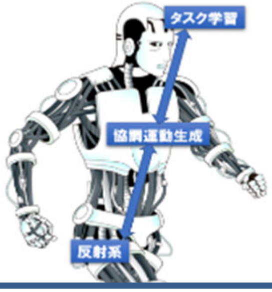
- 高い運動能力を持つ一方で、学習能力を持たない
- 人間のように多様なタスクへの対応が必要



https://www.youtube.com/watch?v=fRj34o4hN4I&t=28s

プロジェクトの概要

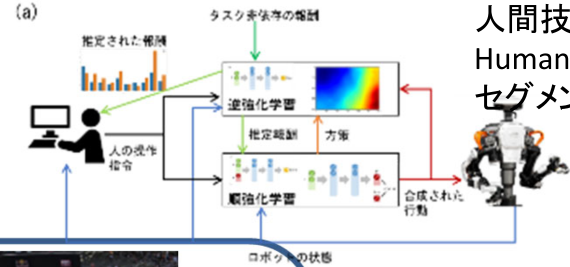
① サイボーグAIプラットフォーム



ハイブリッドアクチュエーション
筋シナジー利用による階層的予測制御

プラットフォーム

②④ 生成的模倣学習・転移学習



人間技能の転移
Human-in-the-loop
セグメンテーション

アルゴリズム

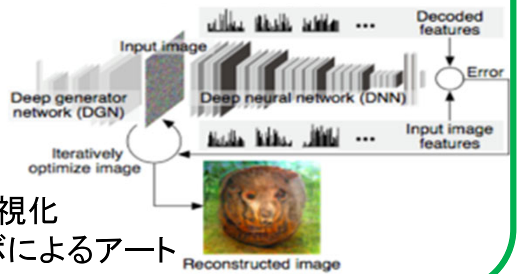
サイボーグAI環境

人との共進化による実時間性、高自由度学習機能の評価

共進化の応用

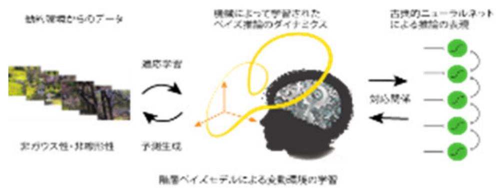
機械学習の数理

③ 三次元空間イマジネーション



空間認識の可視化
人間ーAIコラボによるアート

⑤ 非線形ベイズネットワーク



低次元化したセグメントレベルでの予測・制御

⑥ 運動ダイナミクスの低次元表現

プロジェクトの概要

① サイボーグAIプラットフォーム

ハイブリッドアクチュエーション
筋シナジー利用による階層的予測制御

プラットフォーム

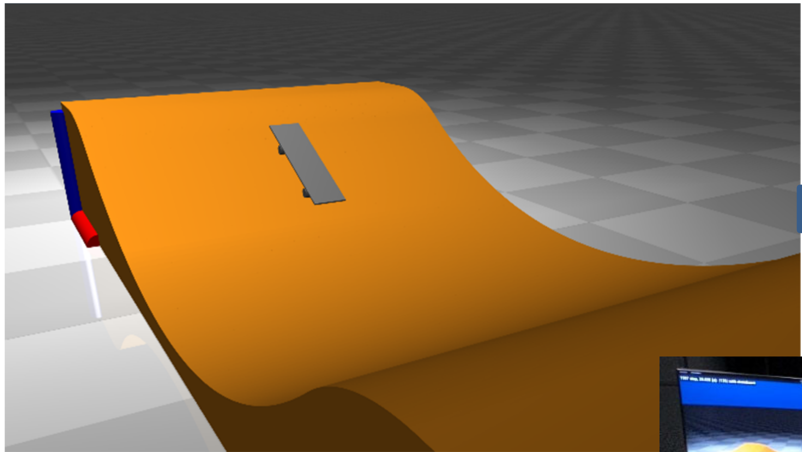
サイボーグAI環境

人との共進化による実時間性、高自由度学習機能の評価

Human Skating

- We are particularly interested in how humans can generate agile movements by smoothly exchanging potential and kinetic energies.

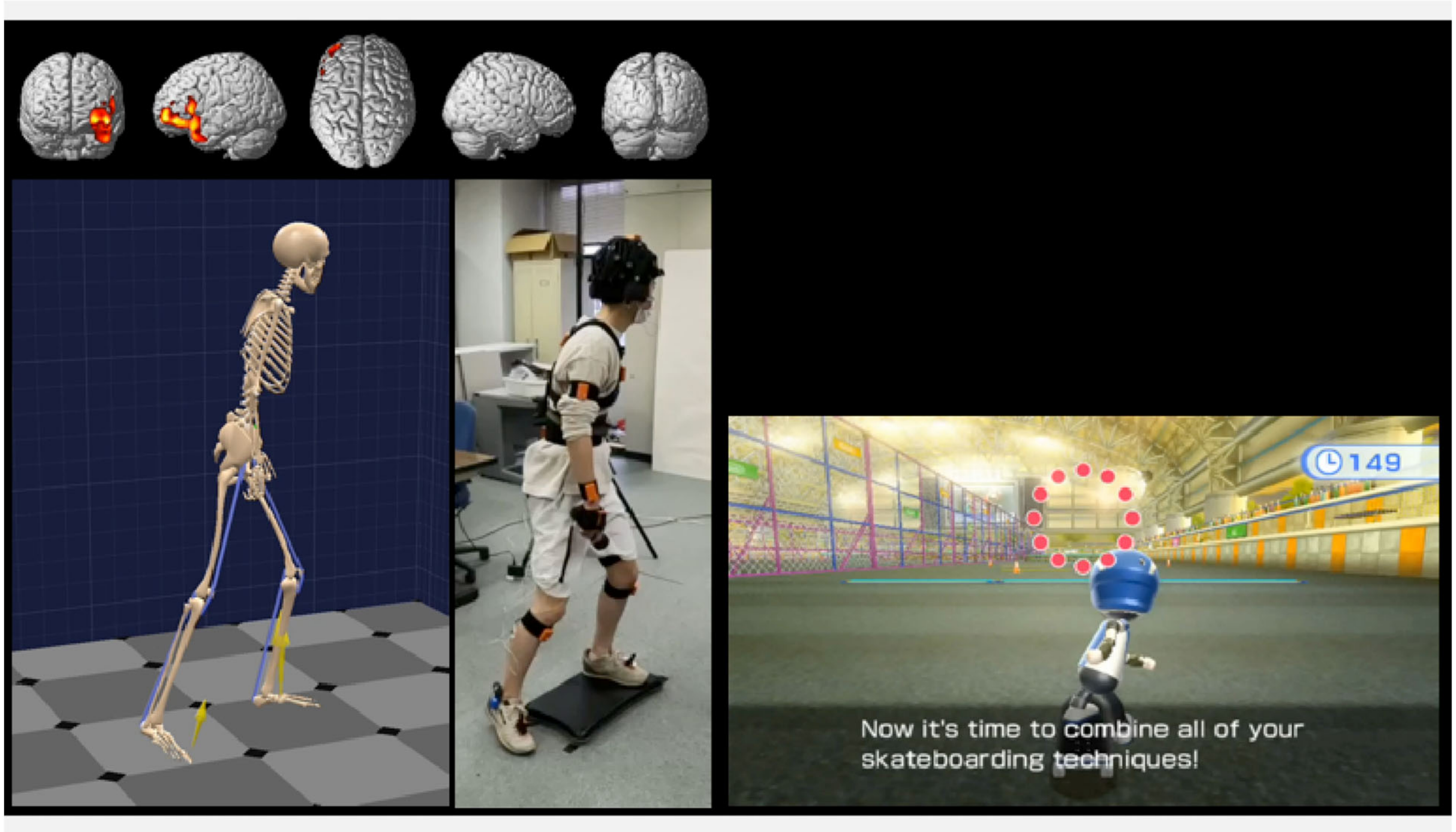
プラットフォーム・環境の開発



サイバー環境

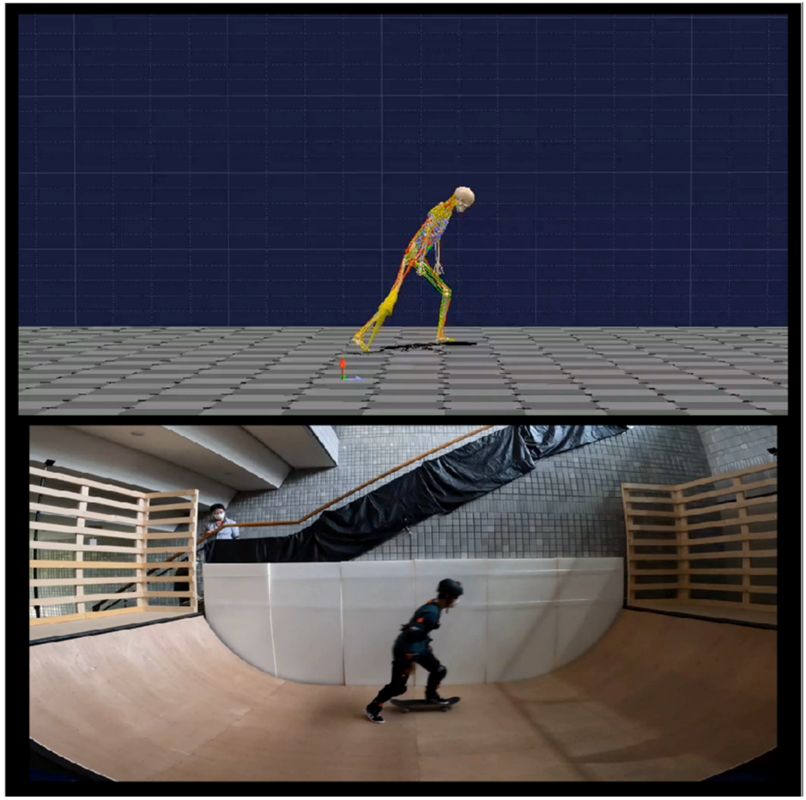
実環境

人間の運動解析


149
Now it's time to combine all of your skateboarding techniques!

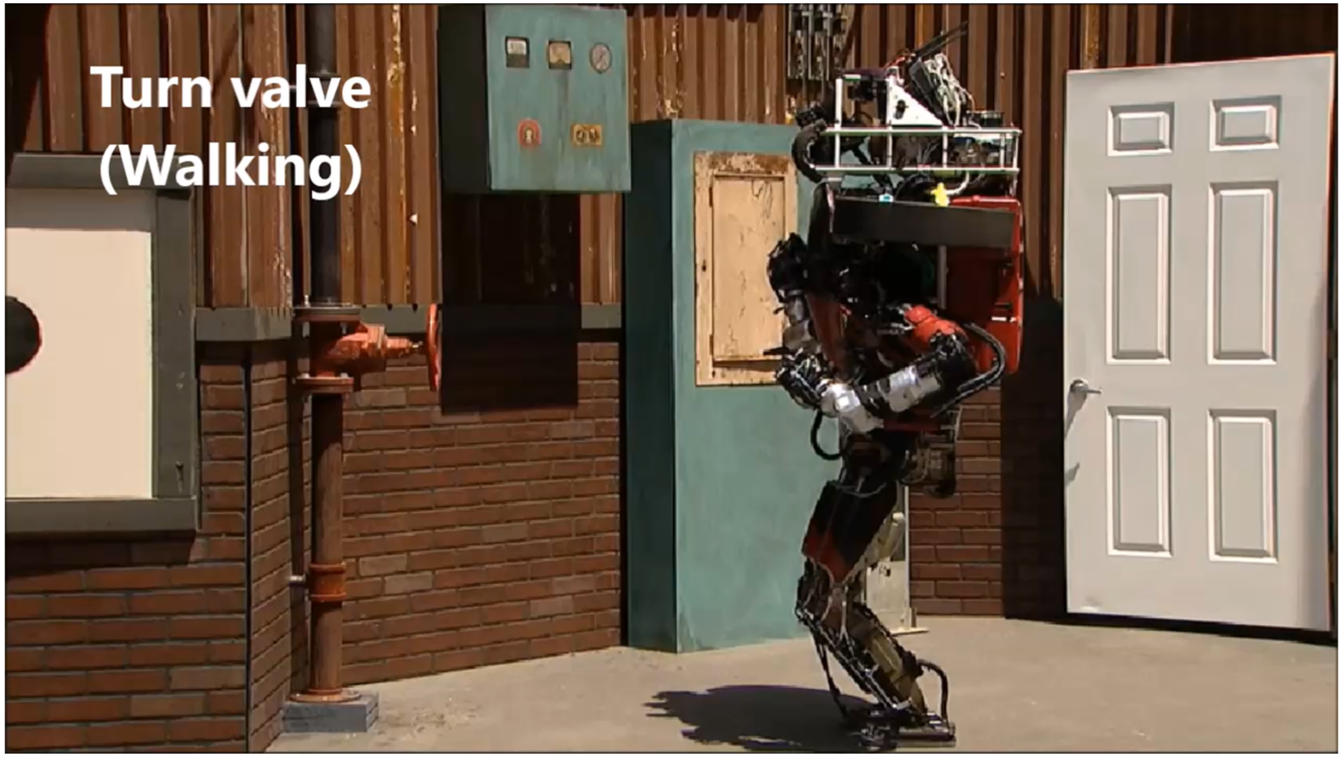
人間の運動解析

ヒトの小さい時定数での制御メカニズムの解析とロボットへの応用



人間エキスパートの運動
D. Callan (ATR)

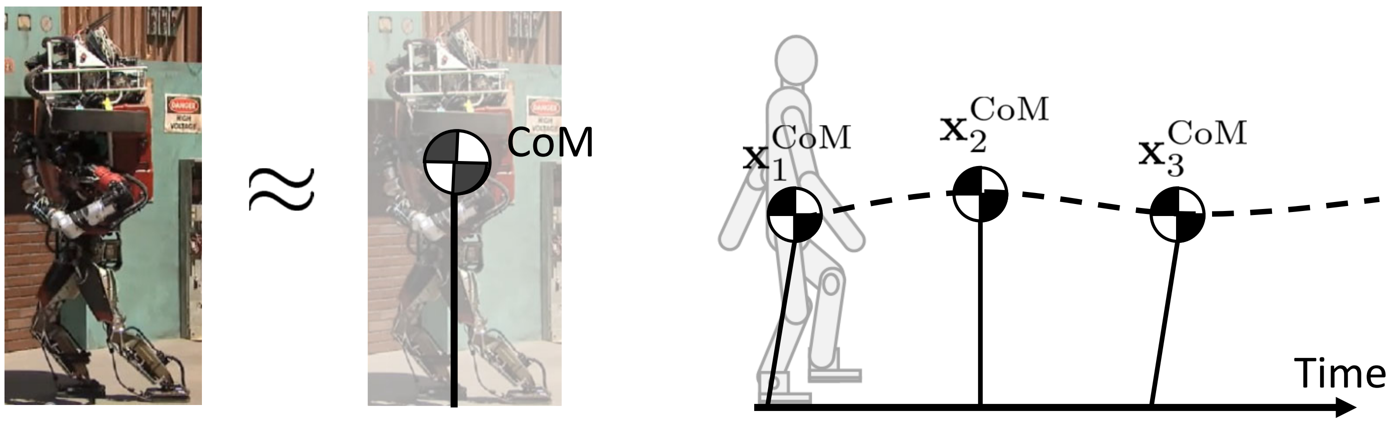
Conventional Humanoid Control Strategy



"An area that leaves much room for robot improvement is in speed of task execution."

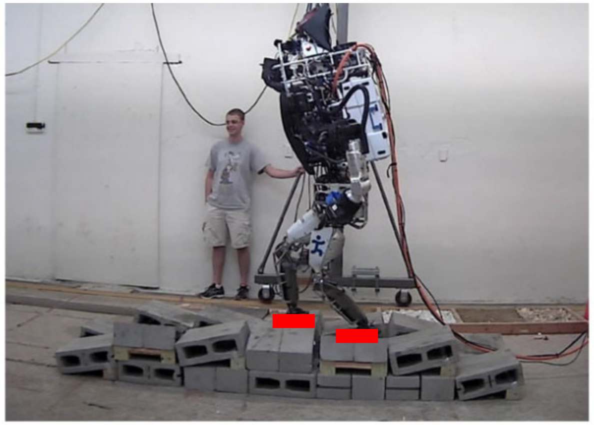
[E. Krotkov, J. FIELD ROBOT, 2017]

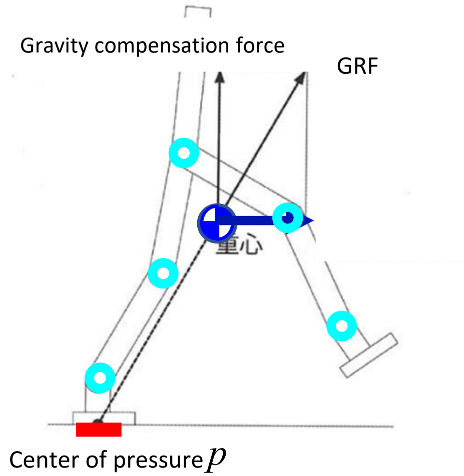
Conventional Humanoid Control Strategy



重心（質点）と床反力の関係で近似.

従来の二足歩行制御のアプローチ





CoM: Center of Mass

x_h^{CoM} ：重心（水平成分）

x_v^{CoM} ：重心（鉛直成分）

g ：重力

p ：床反力中心点

$$p = x_h^{CoM} - \frac{x_v^{CoM}}{g}\ddot{x}_h^{CoM}$$

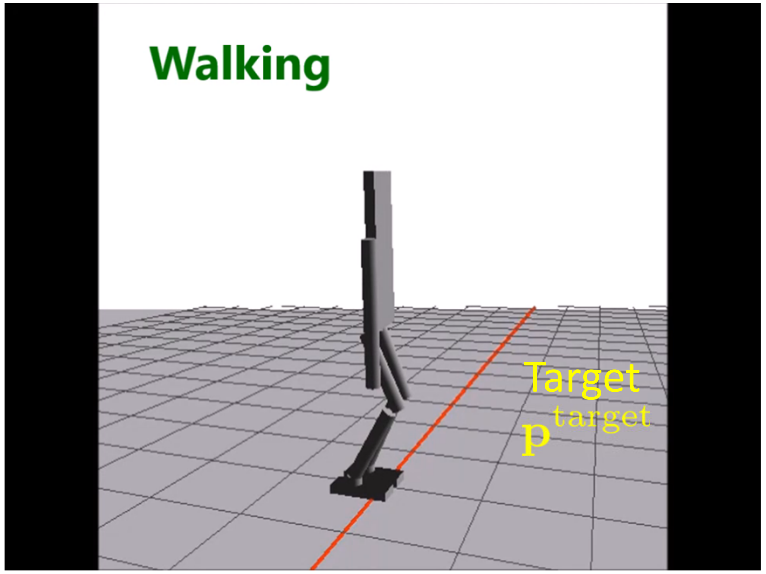
従来の二足歩行制御の アプローチ

- 重心の挙動に着目したモデル:

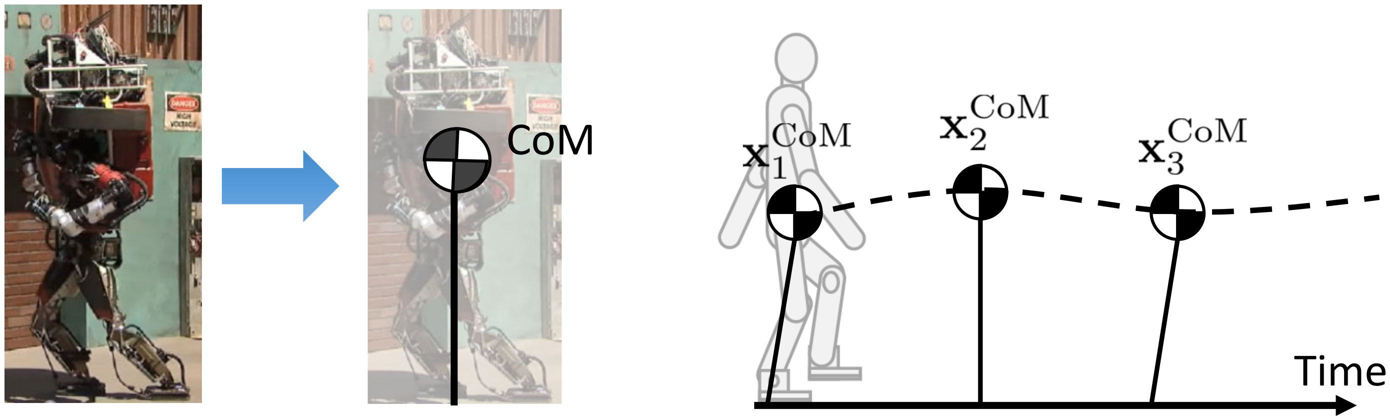
[S. Feng, C. G. Atkeson, *J. FIELD ROBOT*, 2014]

- 逆運動学を用いた四肢の動作生成：

$$\mathbf{x}^{\mathrm{Arm}} \leftarrow \mathrm{IK}(\mathbf{p}^{\mathrm{target}})$$

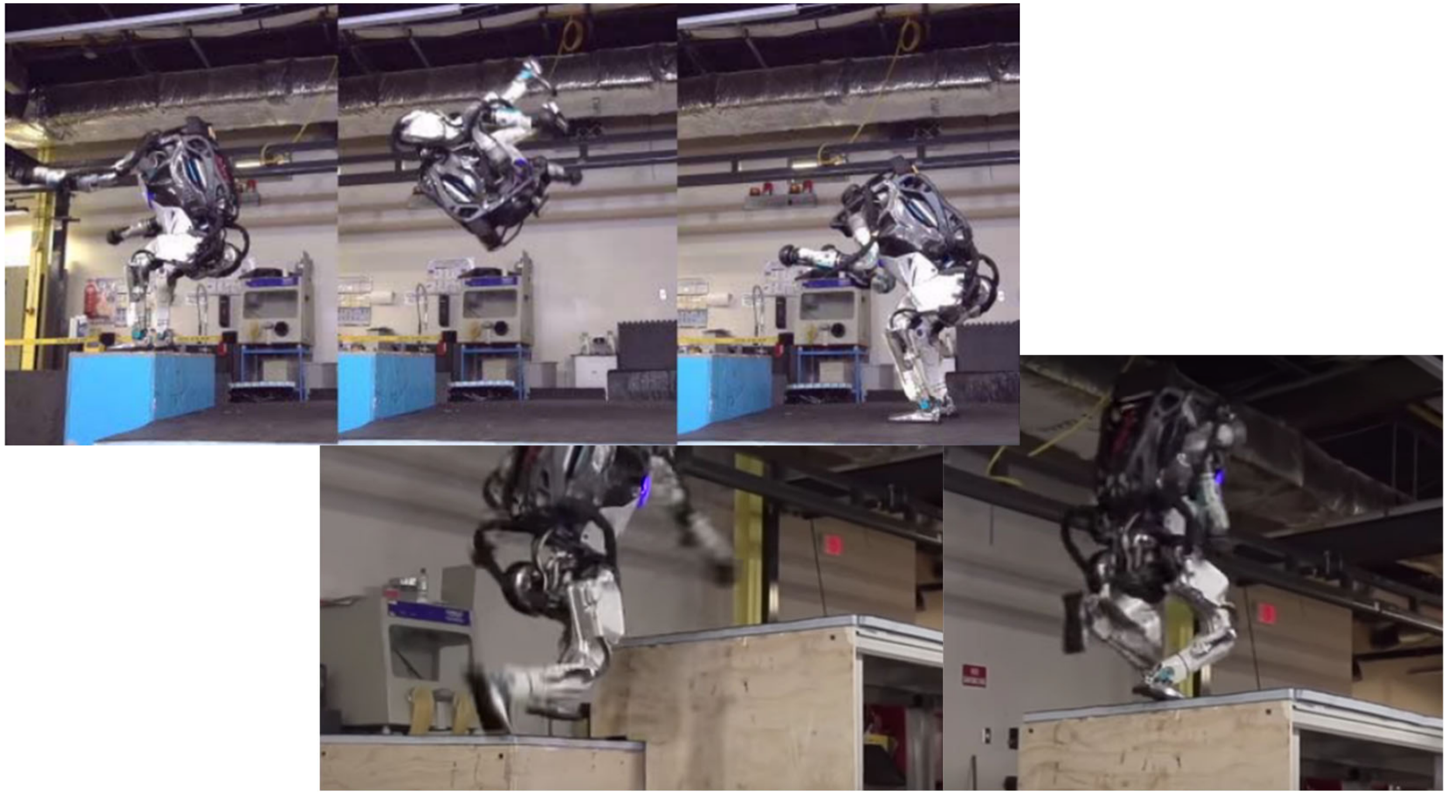


実システムとの誤差を少なくするための取り得るアプローチ



実ロボットの力学系をむしろ，一質点モデルに近づける.

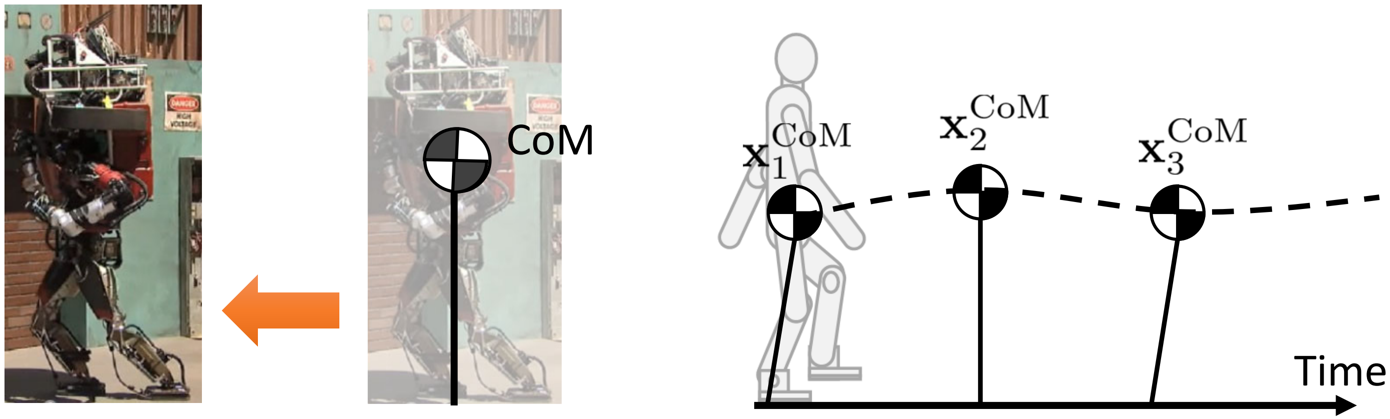
実システムとの誤差を少なくするための取り得るアプローチ



Biped Gymnastics

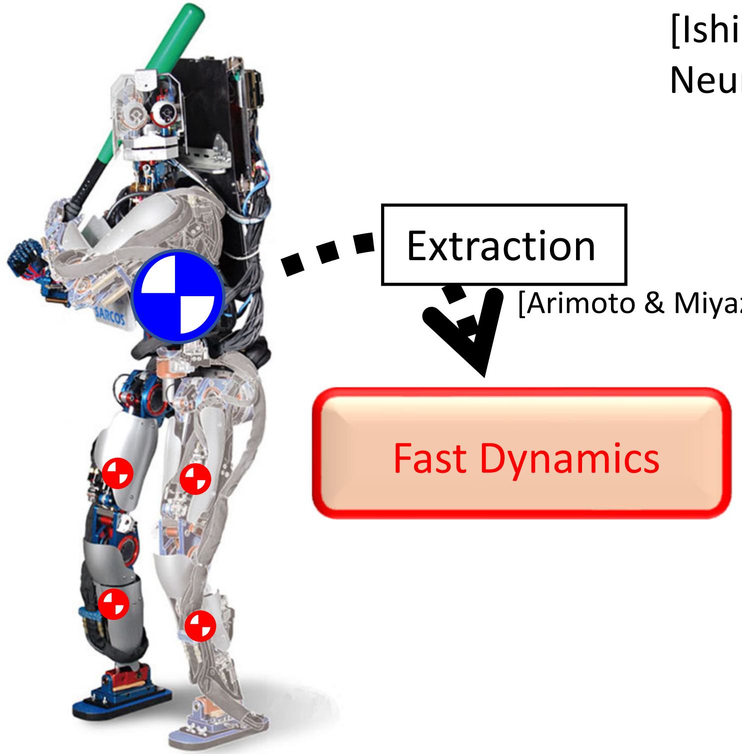
Hodgins, J., Raibert, M. H., Biped gymnastics,
International J. Robotics Research, 9:(2) 115—132,1990

Our Approach



Hierarchical MPC Strategy with Singular Perturbed System

[Ishihara and Morimoto, Humanoids, 2015, Neural Networks, 2018 , IEEE/RAS RA-L, 2020]



特異摂動法を用いて導き出されるヒューマノイドロボットモデルの時間的階層性に着目する.

Hierarchical MPC Strategy with Singular Perturbed System

Original dynamics

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u})$$

$\mathbf{x}$: state
$\mathbf{u}$: control input

Singular perturbed system

$$\dot{\mathbf{y}} = \mathbf{g}(\mathbf{y}, \mathbf{z}, \mathbf{u})$$

$$\varepsilon \dot{\mathbf{z}} = \mathbf{h}(\mathbf{y}, \mathbf{z}, \mathbf{u})$$

$$(0 < \varepsilon \ll 1)$$

$\mathbf{y}$: slow state
$\mathbf{z}$: fast state
$\mathbf{u}$: control input

$$\tau = \frac{t}{\varepsilon}$$

$$\varepsilon = \frac{dt}{d\tau}$$

Fast dynamics

$$\mathbf{y}' = \mathbf{0}$$

$$\mathbf{z}' = \mathbf{h}(\mathbf{y}, \mathbf{z}, \mathbf{u})$$

$$\mathbf{y}' = \varepsilon \mathbf{g}(\mathbf{y}, \mathbf{z}, \mathbf{u})$$

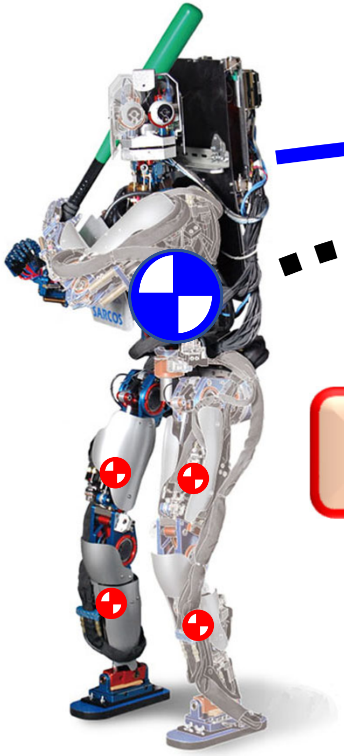
$$\varepsilon \to 0$$

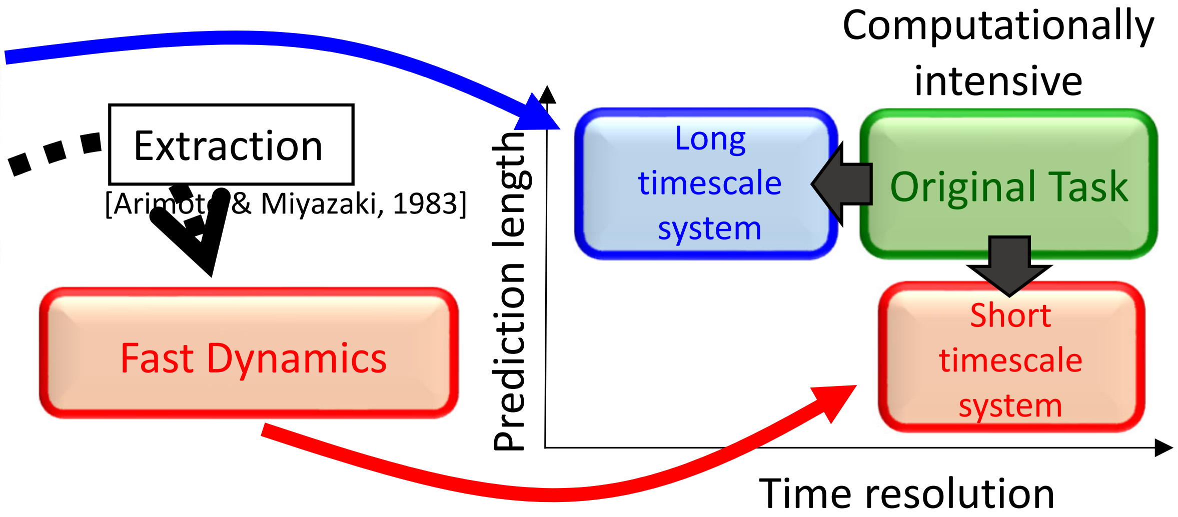
$$\mathbf{z}' = \frac{d}{d\tau}\mathbf{z}$$

$$\dot{\mathbf{y}} = \frac{d}{dt}\mathbf{y} = \frac{d\tau}{dt}\frac{d}{d\tau}\mathbf{y} = \frac{1}{\varepsilon}\mathbf{y}'$$

Hierarchical MPC Strategy with Singular Perturbed System

[Ishihara and Morimoto, Humanoids, 2015, Neural Networks, 2018, IEEE/RAS RA-L, 2020]





Model Predictive Control (MPC)

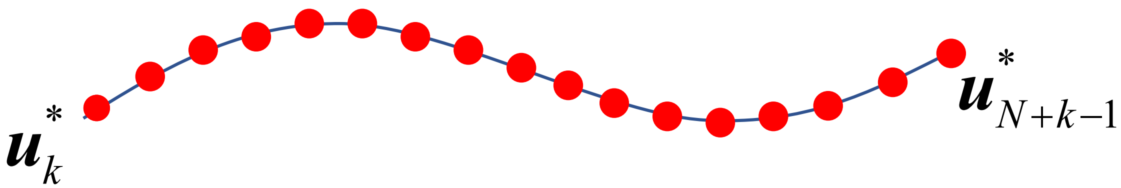
- Online derivation of the optimal control trajectory at each time step, using the first control output.
- Although each optimal control trajectory provides feedforward controller, MPC effectively works as feedback control policy due to the optimal control trajectory calculation at each time step.

State $:\boldsymbol{x}_k$

Objective Function:

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

Target dynamics: $\boldsymbol{s.t.}\ \boldsymbol{x}_{i+1} = \boldsymbol{f}(\boldsymbol{x}_i, \boldsymbol{u}_i)$



Model Predictive Control (MPC)

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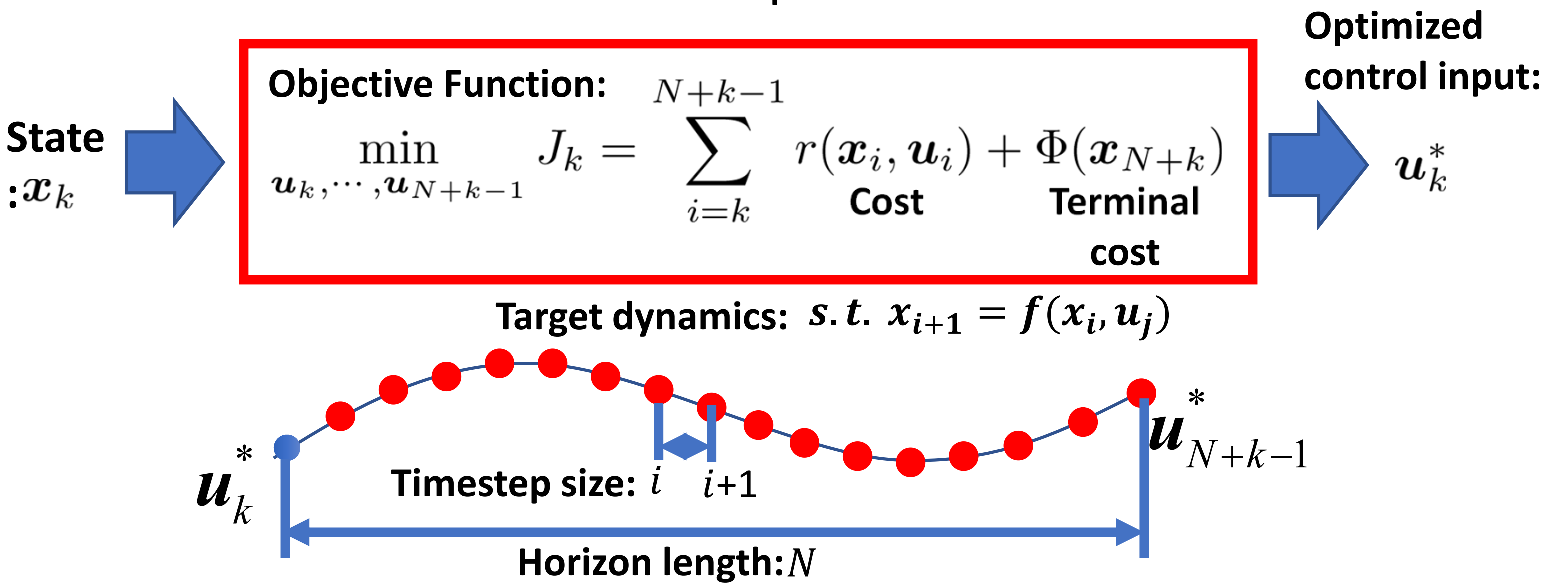
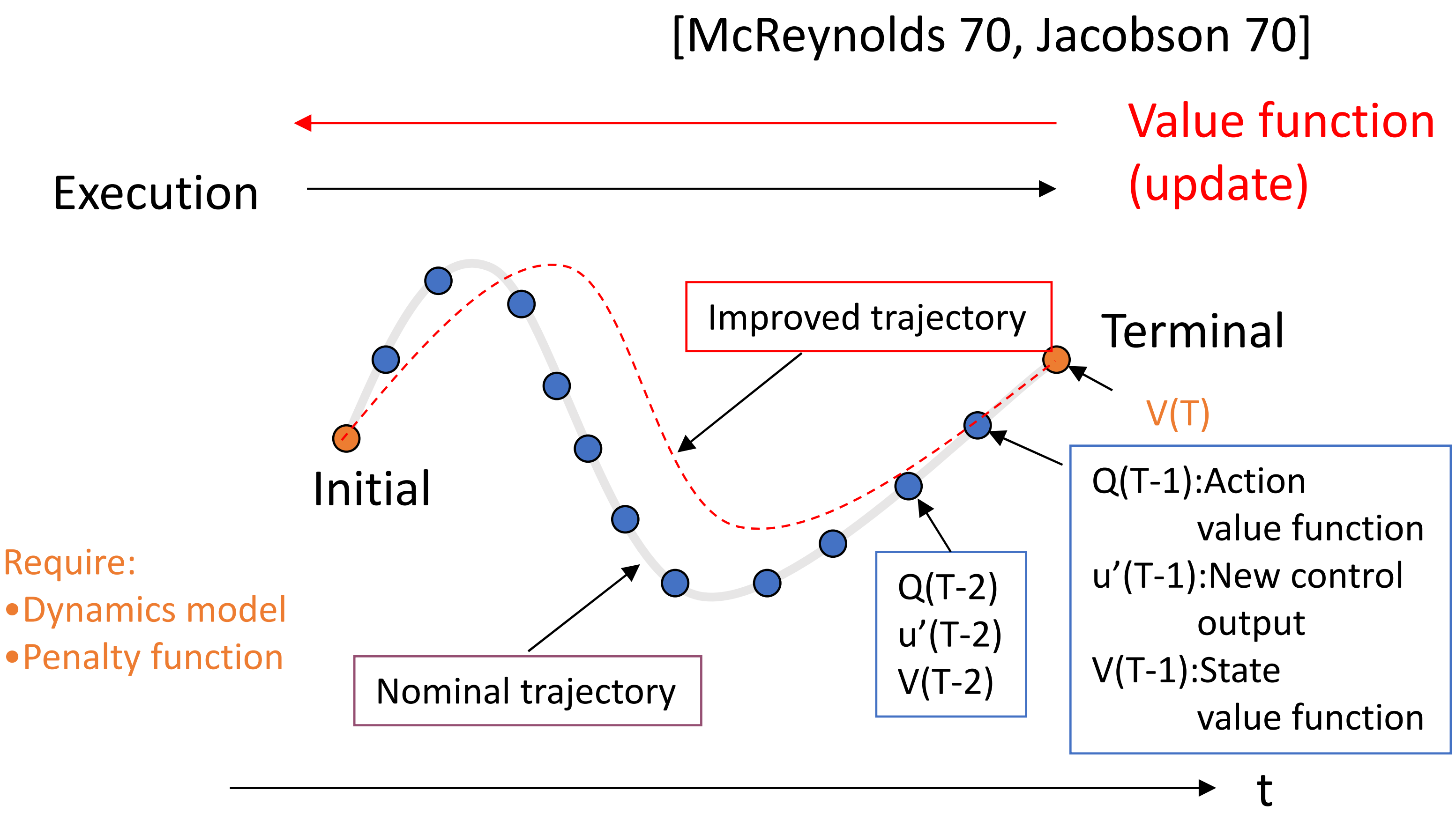
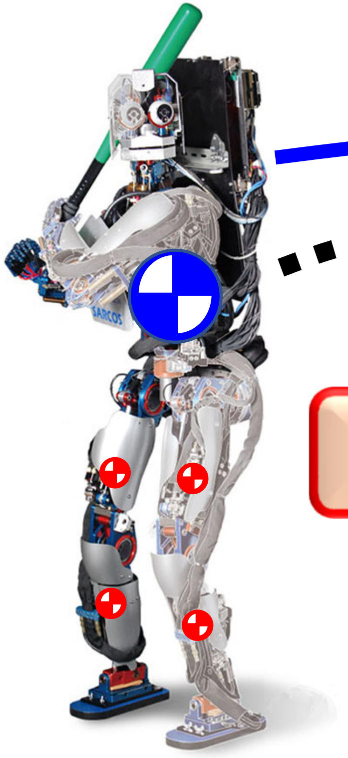


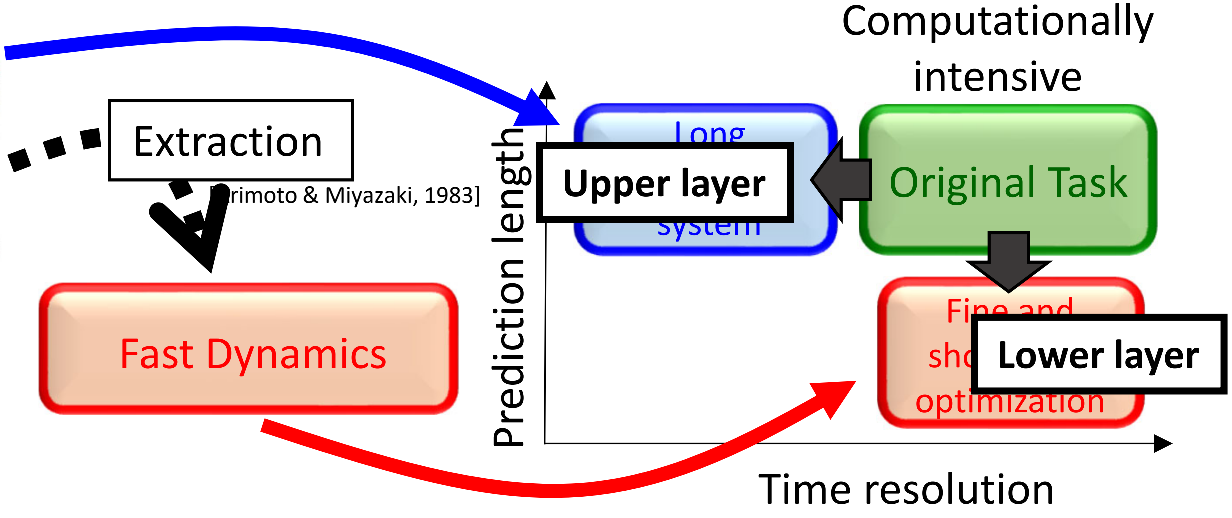
微分動的計画法

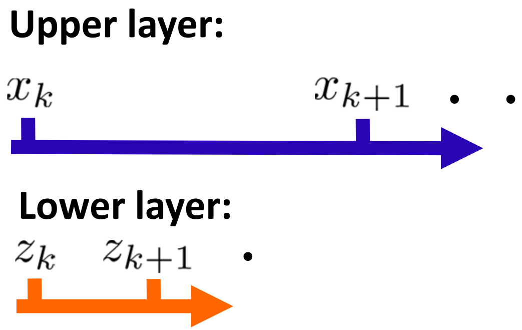

[McReynolds 70, Jacobson 70]
Value function
(update)
Execution
Improved trajectory
Terminal
V(T)
Initial
Q(T-1):Action value function
u’(T-1):New control output
V(T-1):State value function
Q(T-2)
u’(T-2)
V(T-2)
Require:
•Dynamics model
•Penalty function
Nominal trajectory
t

Hierarchical MPC Strategy with Singular Perturbed System

[Ishihara and Morimoto, Humanoids 2015, Neural Networks 2018, IEEE/RAS RA-L 2020]



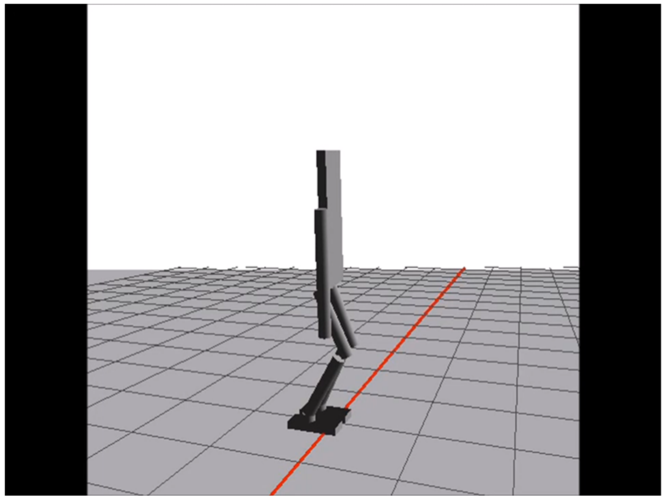




Results

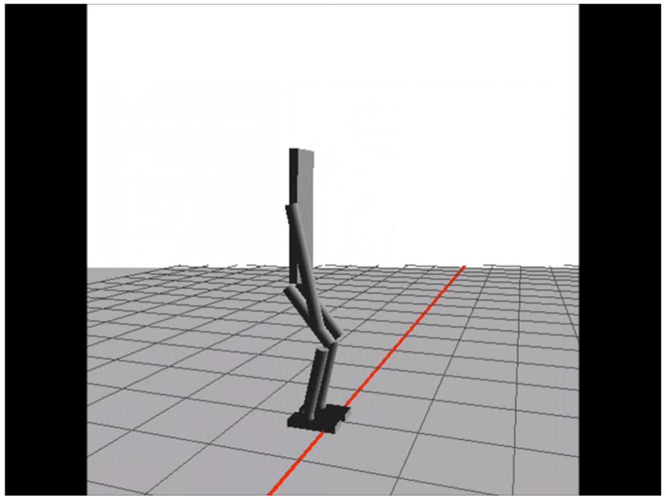
Conventional approach

[S. Feng, C. G. Atkeson, *JFR*, 2014]



Proposed method

Hierarchical MPC

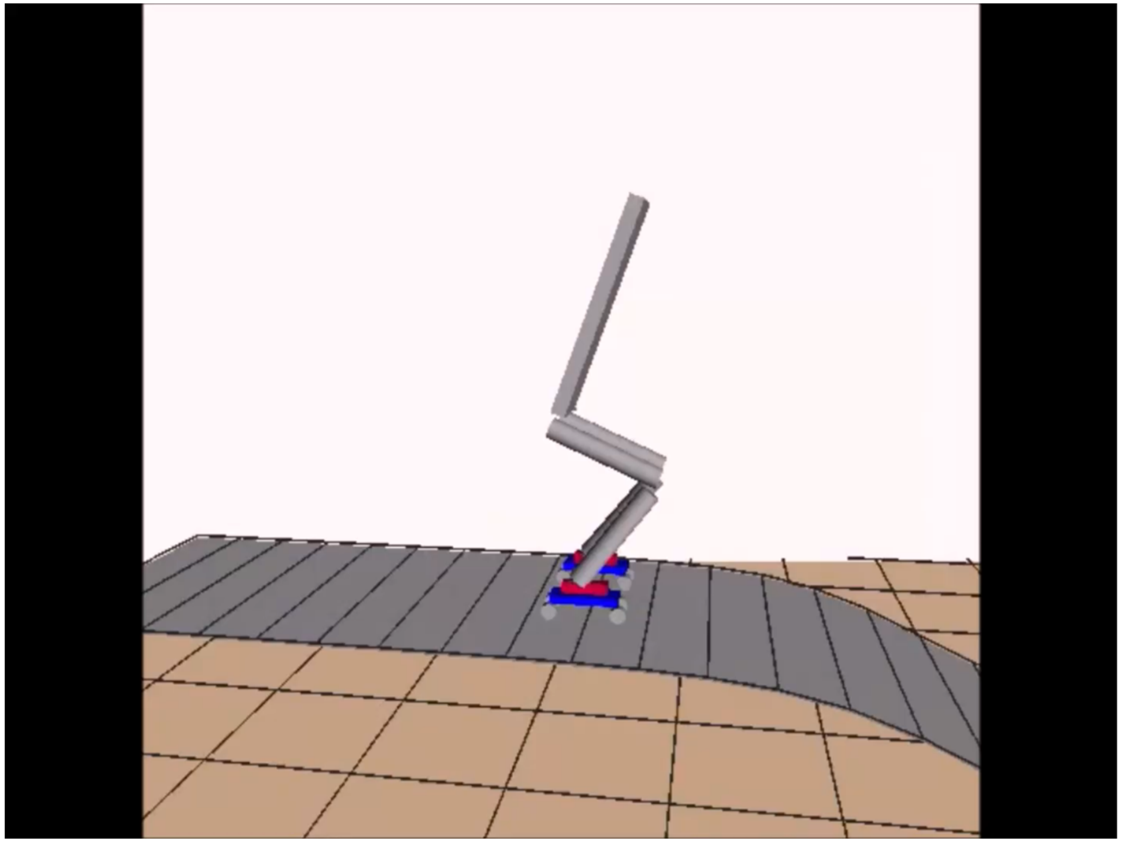


The required time to minimize the distance between the arm and target:

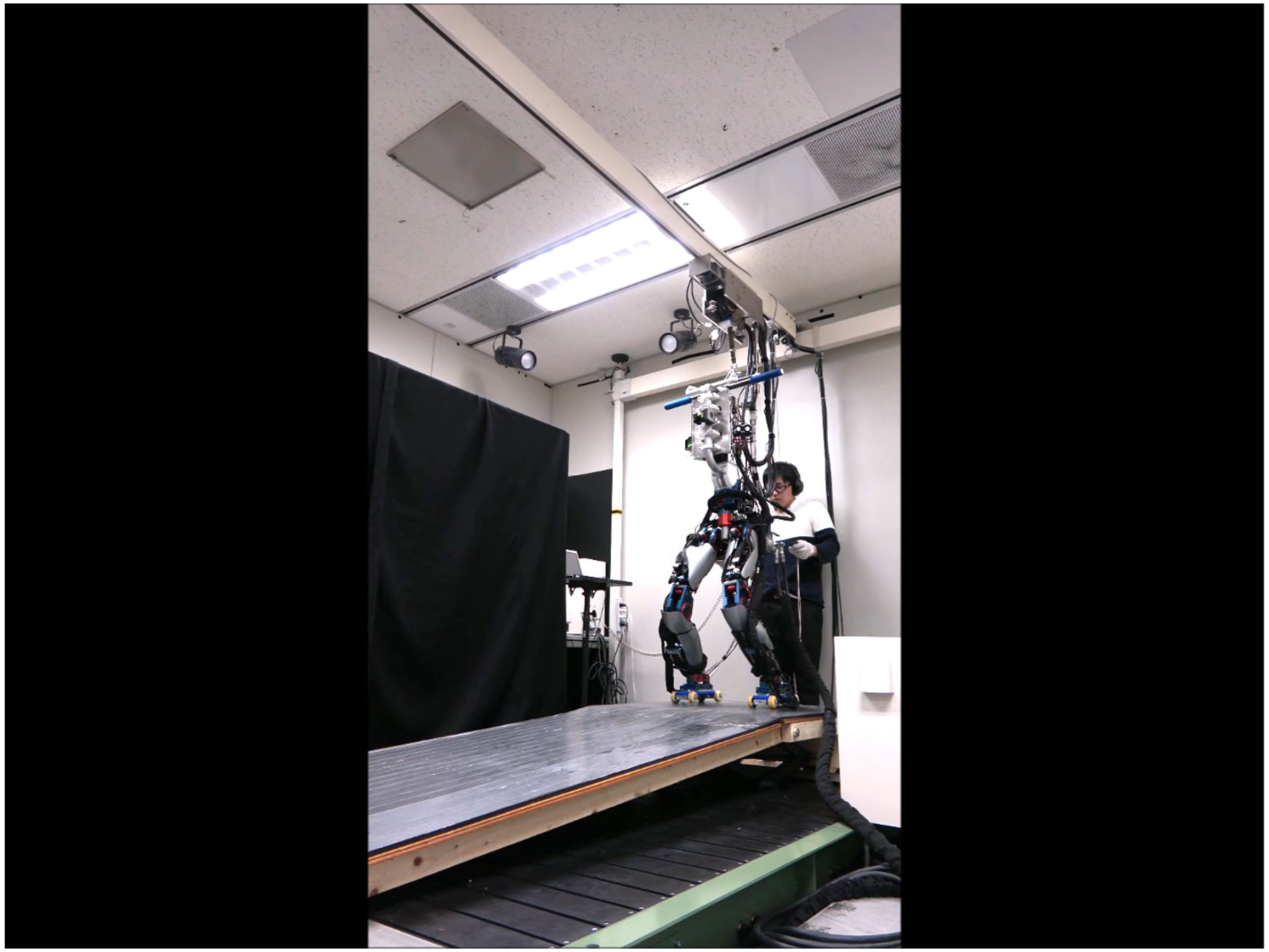
4.4 [s]

1.7 [s]

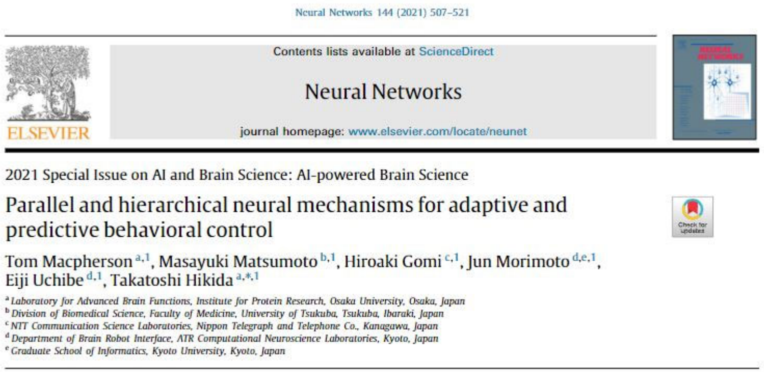
俊敏な動作の生成



Real Robot Control



階層・並列的な行動生成戦略



Neural Networks 144 (2021) 507–521

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Neural Networks

journal homepage: www.elsevier.com/locate/neunet

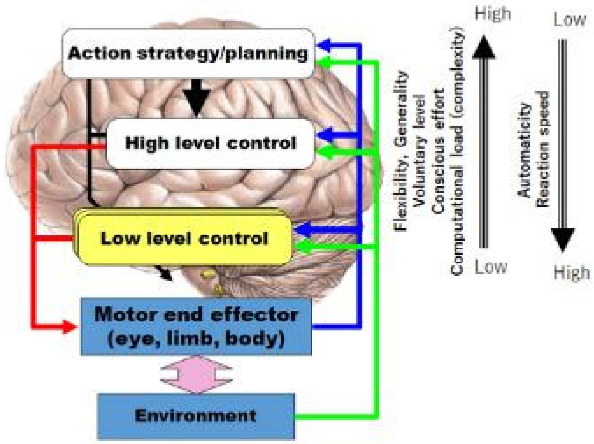
2021 Special Issue on AI and Brain Science: AI-powered Brain Science

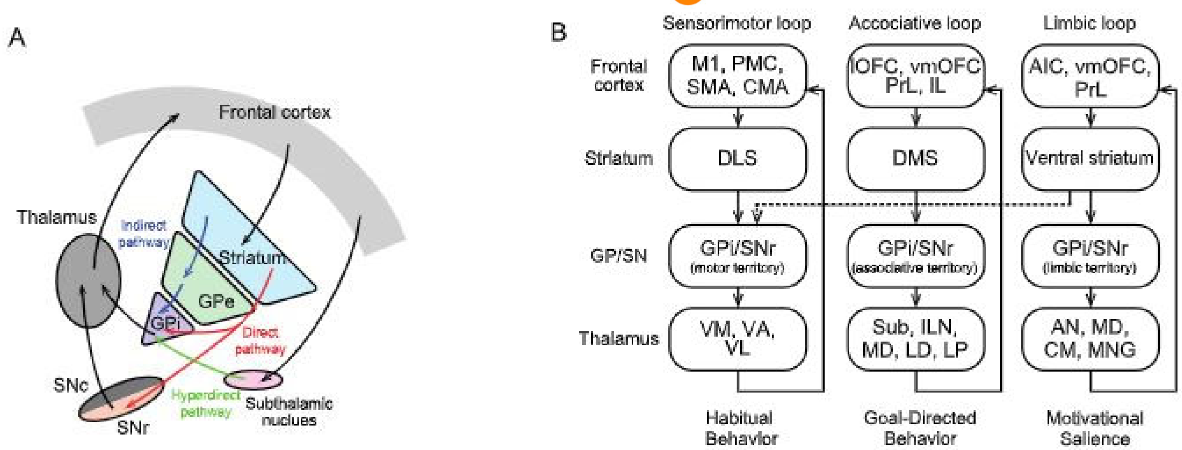
Parallel and hierarchical neural mechanisms for adaptive and predictive behavioral control

Tom Macpherson[a,1], Masayuki Matsumoto[b,1], Hiroaki Gomi[c,1], Jun Morimoto[d,e,1], Eiji Uchibe[d,1], Takatoshi Hikida[a,*,1]

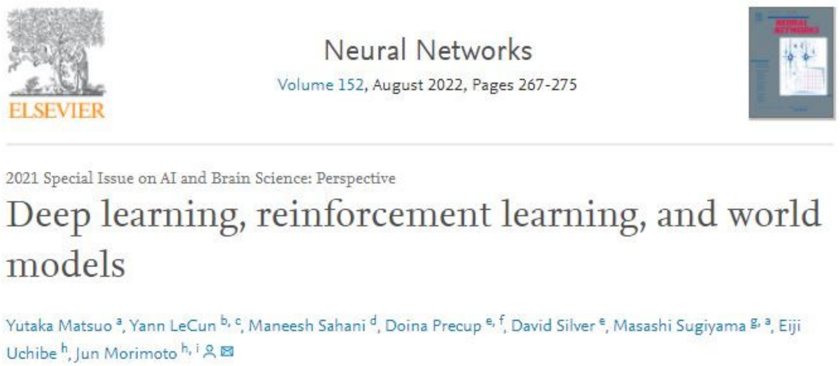
[a] Laboratory for Advanced Brain Functions, Institute for Protein Research, Osaka University, Osaka, Japan
[b] Division of Biomedical Science, Faculty of Medicine, University of Tsukuba, Tsukuba, Ibaraki, Japan
[c] NTT Communication Science Laboratories, Nippon Telegraph and Telephone Co., Kanagawa, Japan
[d] Department of Brain Robot Interface, ATR Computational Neuroscience Laboratories, Kyoto, Japan
[e] Graduate School of Informatics, Kyoto University, Kyoto, Japan

[Macpherson, Morimoto et al., ***Neural Networks***, 2021]





深層学習、強化学習、そして世界モデル



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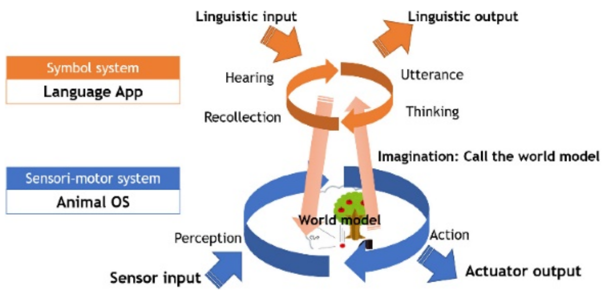
Neural Networks

Volume 152, August 2022, Pages 267-275

2021 Special Issue on AI and Brain Science: Perspective

Deep learning, reinforcement learning, and world models

Yutaka Matsuo [a], Yann LeCun [b, c], Maneesh Sahani [d], Doina Precup [e, f], David Silver [e], Masashi Sugiyama [g, a], Eiji Uchibe [h], Jun Morimoto [h, i]



[Matsuo, Morimoto et al., ***Neural Networks***, 2022]