# DynSyn: Dynamical Synergistic Representation for Efficient Learning and Control in Overactuated Embodied Systems


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## Overview

- Learning an effective policy to control a high-dimensional, overactuated system is very challenging for deep reinforcement learning.
- The neural control of vertebrate musculoskeletal systems will provide insight into the control of these systems.
- We propose a synergy-based representation method of reinforcement learning algorithms to enhance sample efficiency in controlling these systems.

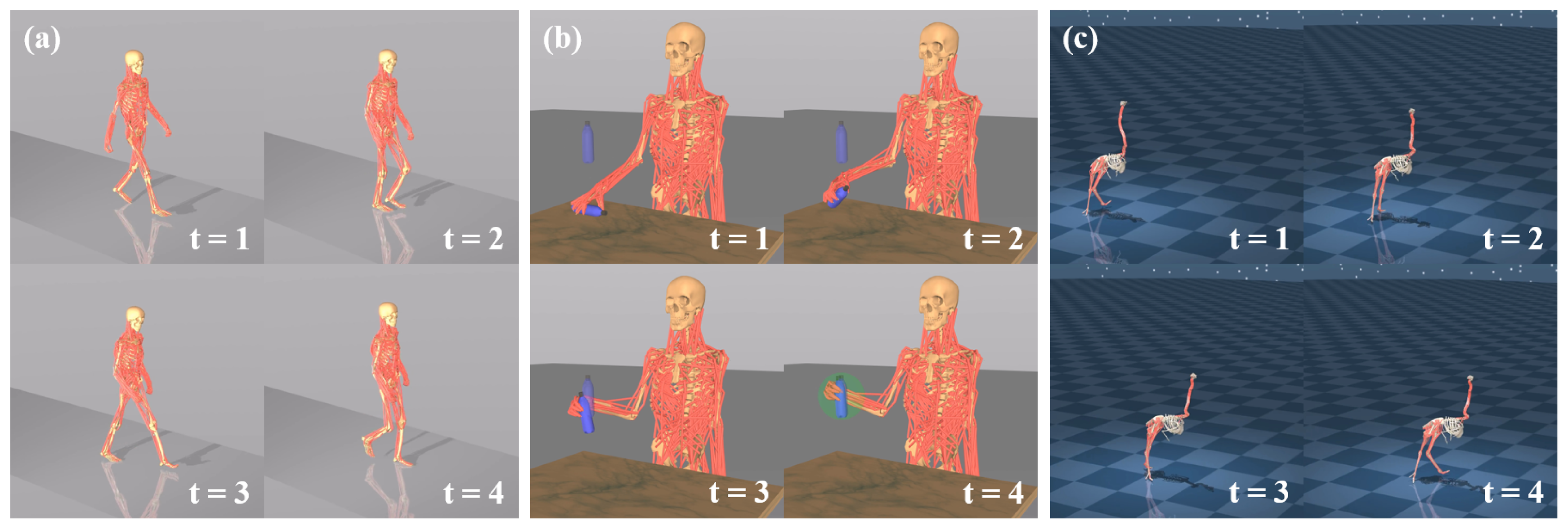



Figure 1. **Motor behaviors of overactuated musculoskeletal systems acquired by DynSyn.** (a) Gait of MS-Human-700 model. (b) Manipulation of Arm model. (c) Locomotion of Ostrich model.

## Background

We perform validation of the algorithm in the musculoskeletal system. In this system, the muscle-tendon units exert tensile forces on bones to move joints.

**Neuro-Muscle Dynamics.** The activation-contraction dynamics of muscles exhibit non-linearity and temporal delay, thereby posing challenges to neuromuscular control. The muscle force produced can be formulated as

$$f_m(act) = f_{max} \cdot [F_l(l_m) \cdot F_v(v_m) \cdot act + F_p(l_m)]. \tag{1}$$

The muscle activation $act$ is calculated by Eq.(2) where $u$ is the input control signal of the musculoskeletal model.

$$\frac{\partial act}{\partial t} = \frac{u - act}{\tau(u, act)}, \tau(u, act) = \begin{cases} \tau_{\text{act}}(0.5 + 1.5act) & u > act \\ \frac{\tau_{\text{deact}}}{0.5+1.5act} & u \leq act \end{cases} \tag{2}$$

## Motivation

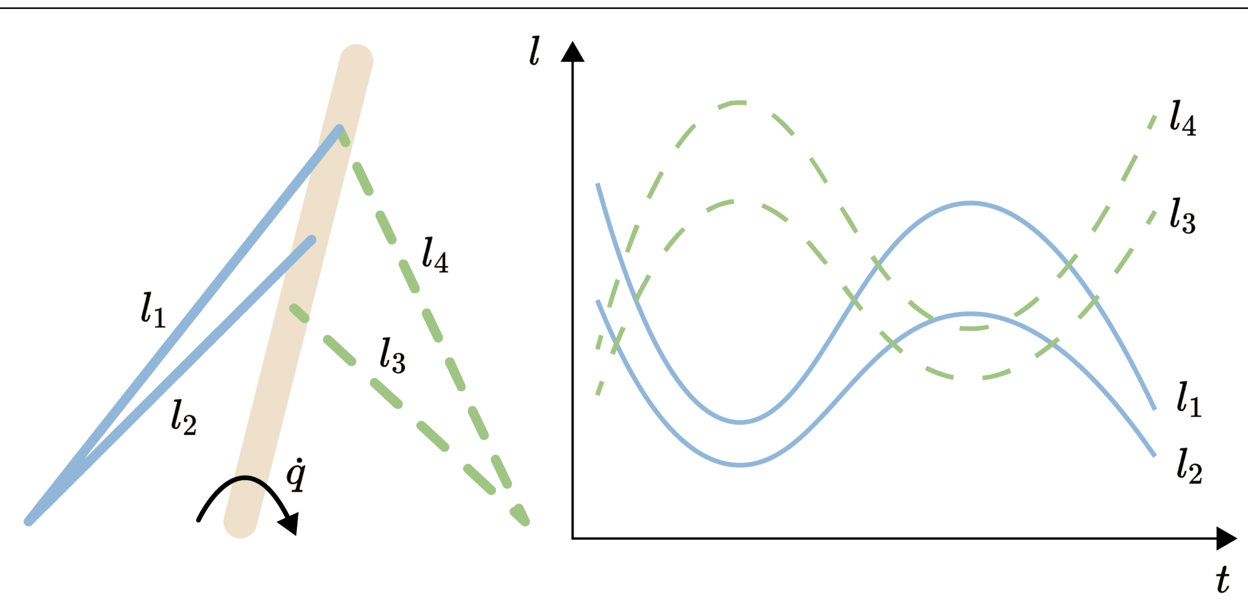



Figure 2. **Motivation of DynSyn.** The brown link represents a robot arm (or bone), while the blue and green lines represent the cable actuators (or muscles). By randomly controlling the joint velocity, the lengths of the four actuators are demonstrated on the right. Actuators with similar functions are categorized into the same group due to similar structures, based on the correlation of length changes.

## Algorithm

### Representation Generation

Disturbances are directly applied at the joints, and clustering is performed based on the cosine similarity of muscle length changes.

$$R_{i,j} = \frac{1}{N} \sum_{k=0}^{N-1} S_c(\tau^i_{[\frac{N_s}{N}k:\frac{N_s}{N}(k+1)]}, \tau^j_{[\frac{N_s}{N}k:\frac{N_s}{N}(k+1)]}) \tag{3}$$

### State-dependent Representation

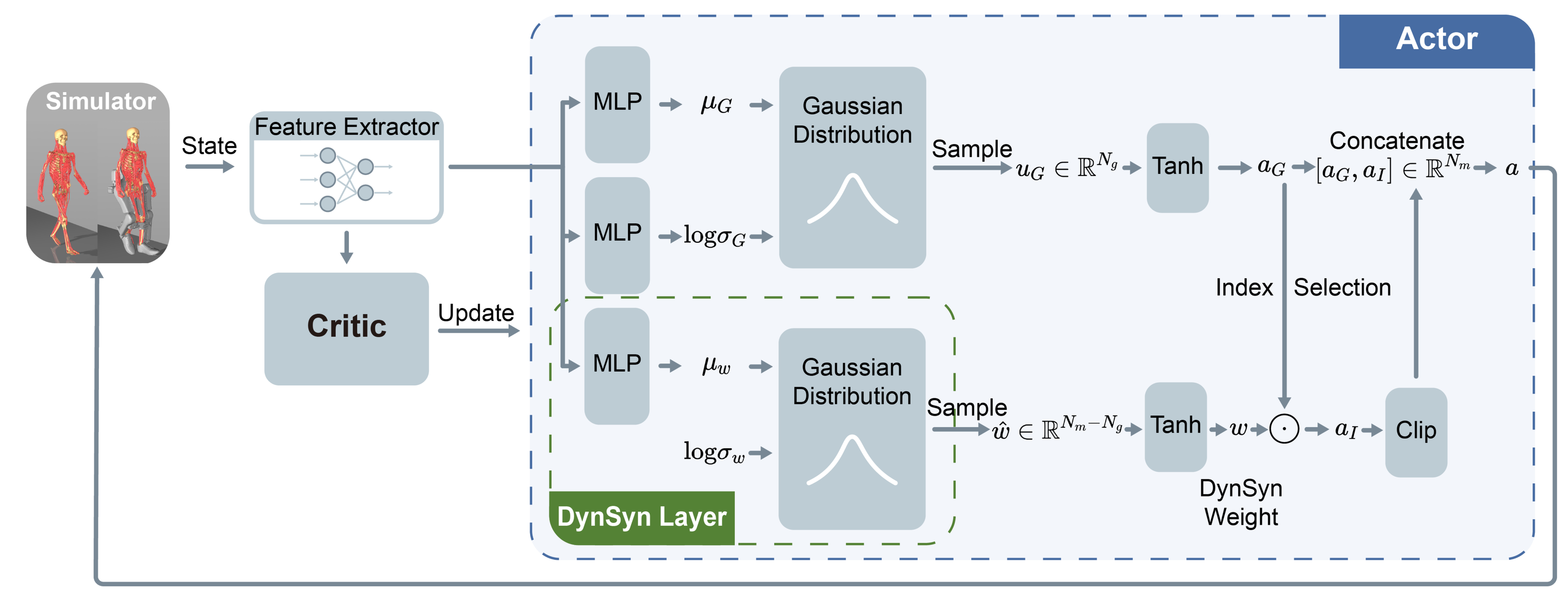



Figure 3. Overview of DynSyn.

The algorithm generates:

1. a unified action $a_G$ for each group of actuators,
2. and state-dependent correction weights $w$ for each actuator on top of the unified action $a_G$.

$$a_G = \tanh(u_G), u_G \sim \mathcal{N}(\mu_G, \sigma_G) \tag{4}$$

$$w = \tanh(\hat{w}), \hat{w} \sim \mathcal{N}(\mu_w, \sigma_w) \tag{5}$$

$$a_I = \text{IS}(a_G) \odot \text{clip}(\kappa w, -c, c) \tag{6}$$

$$c = \min(\max(k_D t + a_D, 0), \kappa) \tag{7}$$

$$a = \text{clip}([a_G, a_I], -1, 1) \tag{8}$$

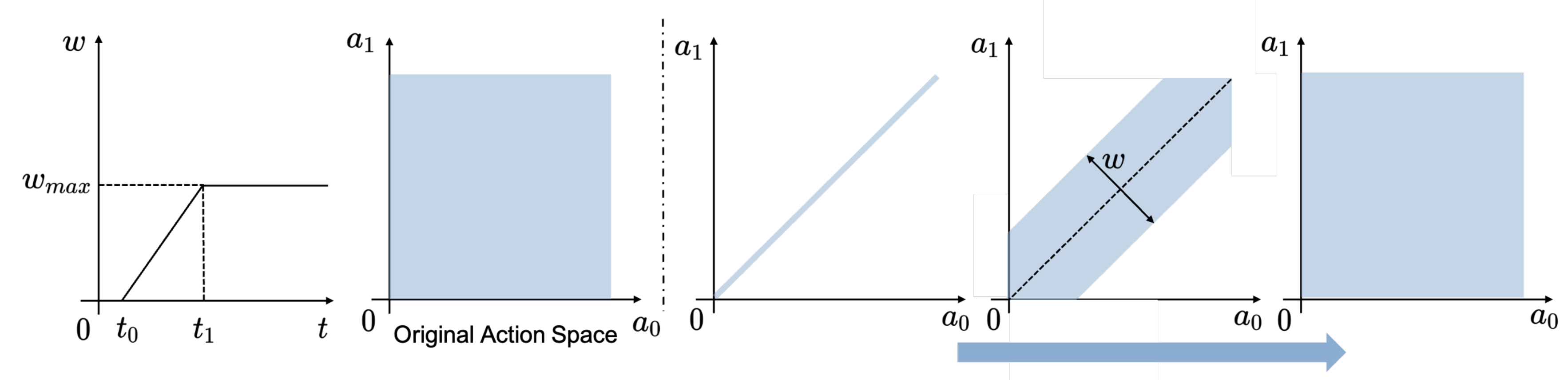



Figure 4. DynSyn Weight Strategy.

## Experiments

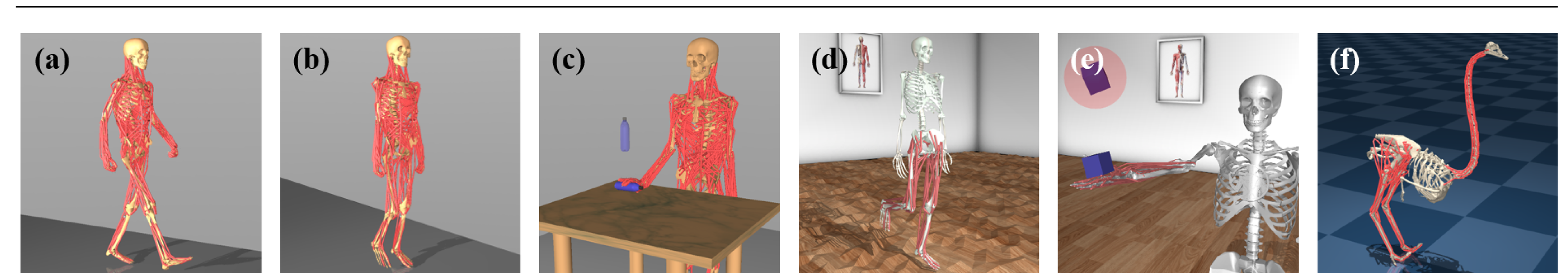
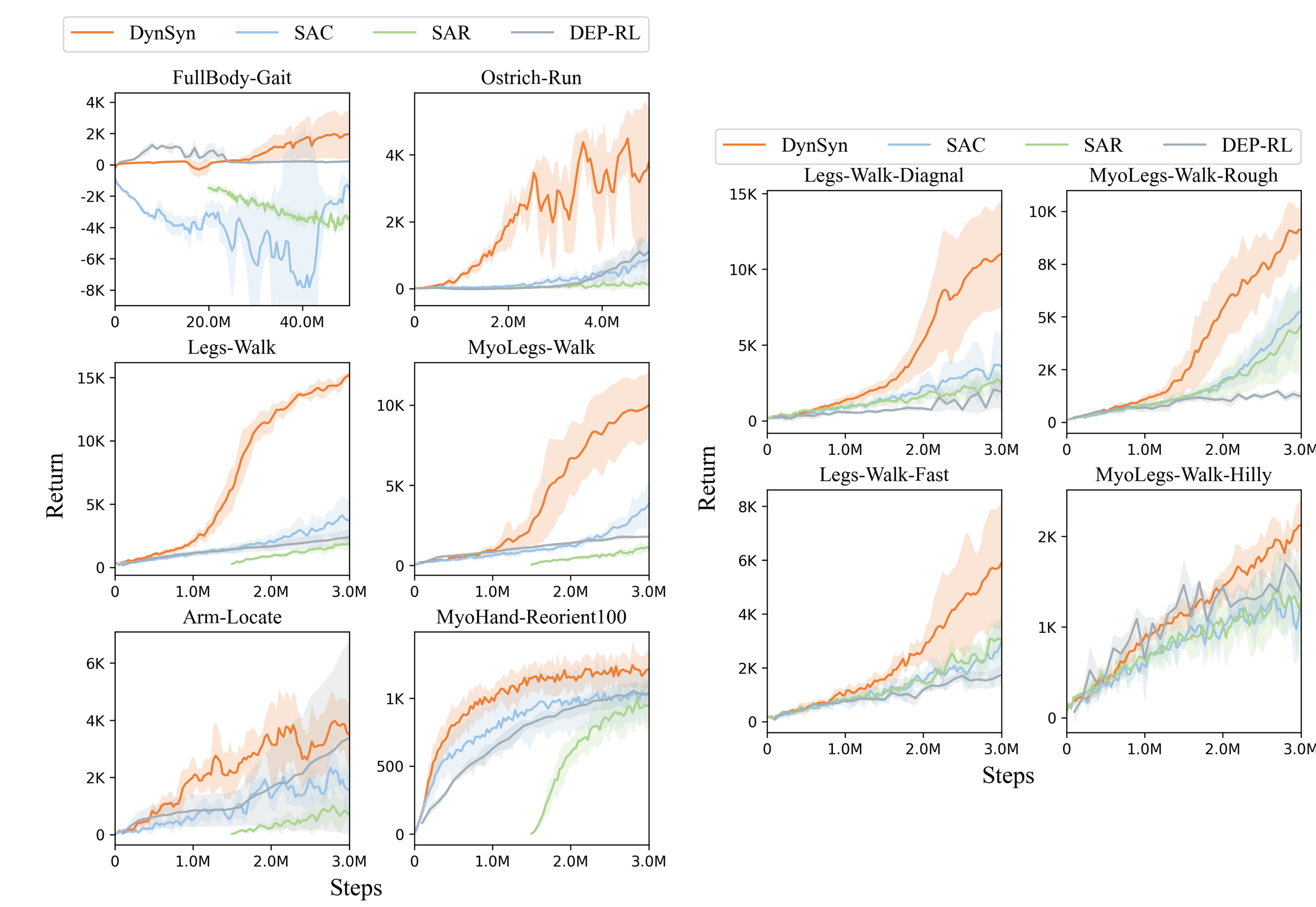



Figure 5. **Experiment environments.** (a) MS-Human-700-Gait ($a \in \mathbb{R}^{700}$). (b) Legs-Walk ($a \in \mathbb{R}^{100}$). (c) Arm-Locate ($a \in \mathbb{R}^{81}$). (d) MyoLegs-Walk w/ rough terrain ($a \in \mathbb{R}^{80}$). (e) MyoHand-Reorient100 ($a \in \mathbb{R}^{39}$). (f) Ostrich-Run ($a \in \mathbb{R}^{120}$).

## Results

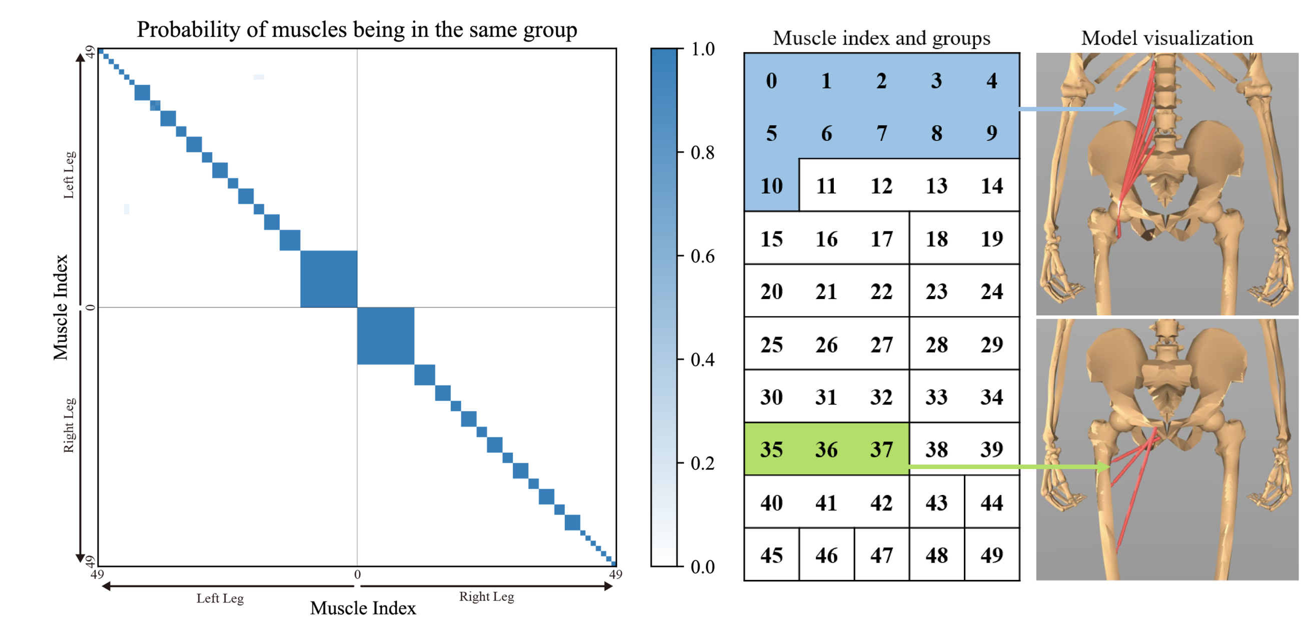
### Sample Efficiency and Generalization Capability




(a) Standard results. (b) Generalization results.

Figure 6. **Learning curves in the experimental environments.**

### Physiological Interpretability




(a) Standard results. (b) Generalization results.

Figure 7. **Muscle grouping of *Legs* model.**

## Conclusion

We propose a new method that generates synergistic representations from dynamical structures and offers efficient, generalizable and interpretable control of high-dimensional overactuated systems.

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