

The background of the slide is a composite image. The top half shows a city skyline at sunset or sunrise, with mountains in the distance. Overlaid on this is a futuristic, glowing blue and green digital cityscape with tall, translucent skyscrapers. A white seagull is flying in the sky. The bottom half of the slide shows a lush green field with some small brown insects or leaves scattered on it.

**SIGGRAPH
2025**

The Premier Conference & Exhibition on
Computer Graphics & Interactive Techniques

PhysicsFC:

**Learning User-Controlled Skills
for a Physics-Based Football Player Controller**

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HANYANG UNIVERSITY**



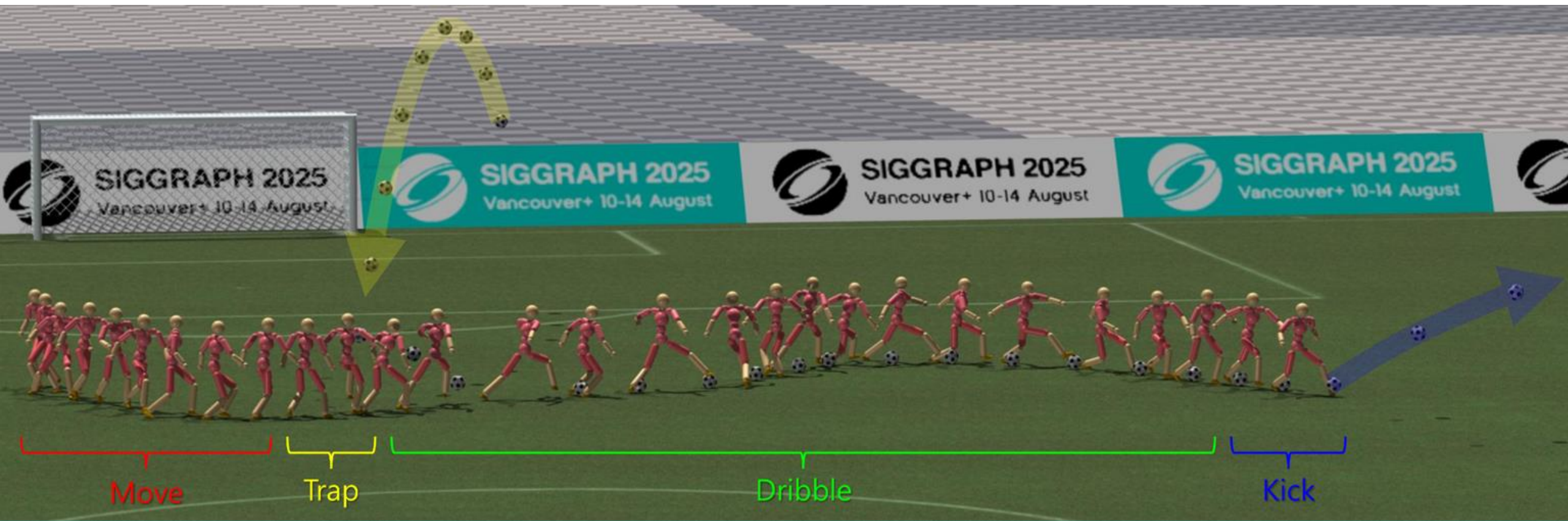
FC Online (FIFA series)



eFootball (Winning Eleven)

- Current football games : kinematic character + physics-based ball
→ Unrealistic character movement!

- We propose **PhysicsFC**, a method for **controlling physically simulated football player characters**.
- Variety of football skills—such as **dribbling, trapping, moving, and kicking**—based on user input.
- **Seamless transition** between these skills.



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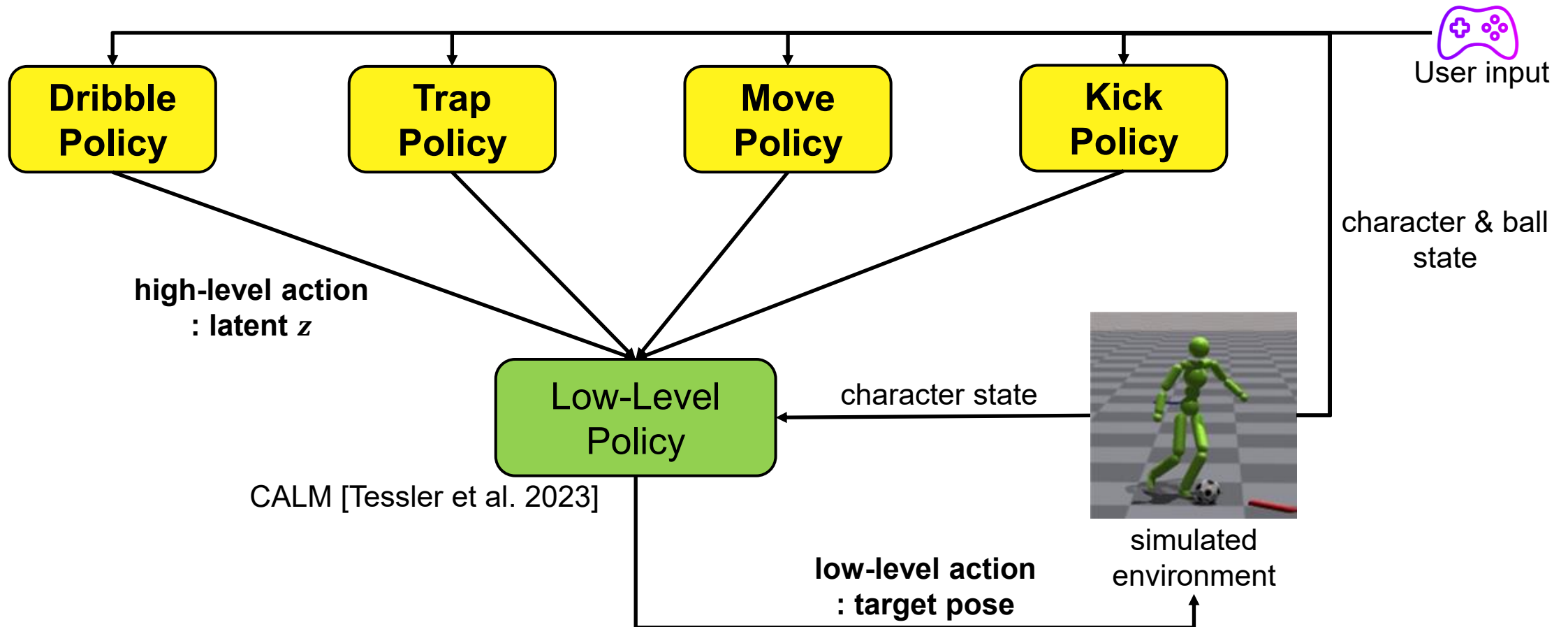
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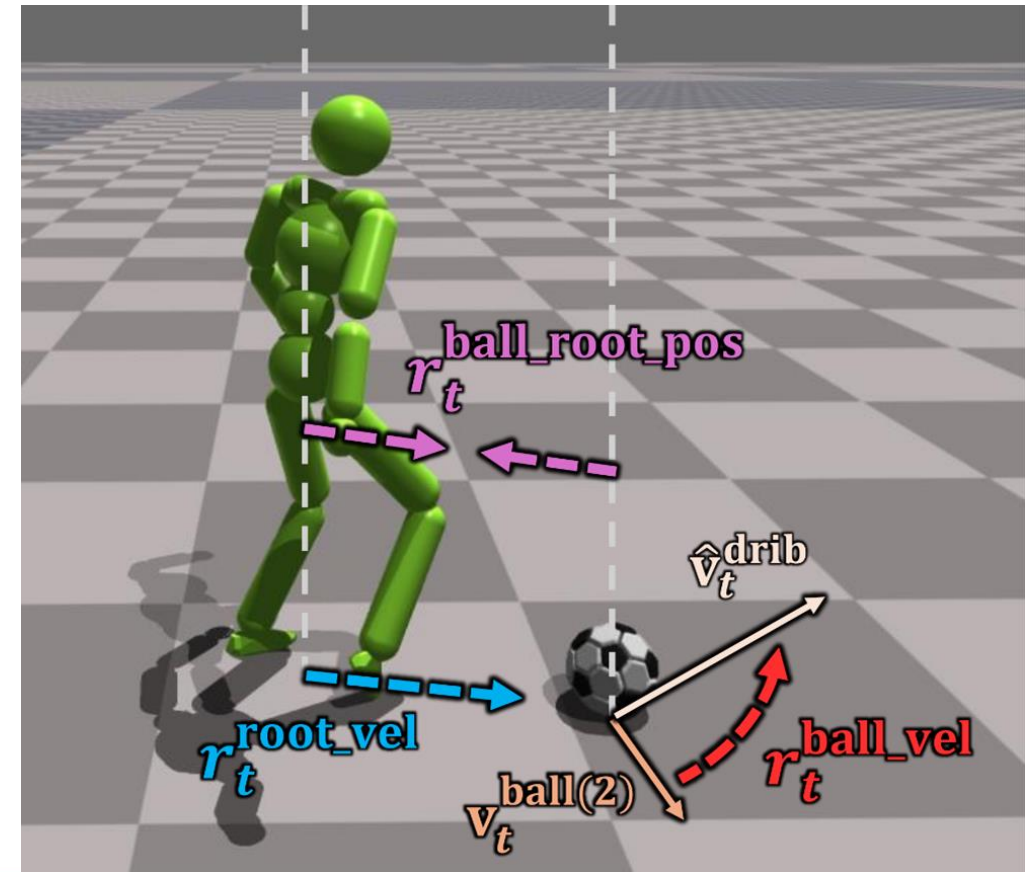
- The character must **follow user commands & interact with the ball.**
→ Use a **hierarchical control structure.**
- The character must perform **various skills.**
→ **Each skill policies** learned with **tailored rewards, initialization, and training.**
- The character must **transition** between skills **smoothly and quickly.**
→ Proposed the **Skill Transition-Based Initialization (STI).**
- Each skill and transition must be **user-controllable** and **context-responsive.**
→ Proposed the football player finite state machine (**PhysicsFC FSM**).

Each skill = separate policy (trained individually)



DRIBBLE POLICY

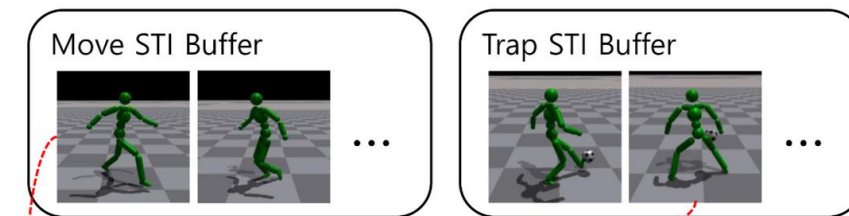
- **Goal** : Dribble at target speed while keeping ball close
- **Input** : Target dribble velocity
- **Reward** : $r_t^{\text{drib}} = 0.6 \underline{r_t^{\text{ball_vel}}} + 0.2 \underline{r_t^{\text{ball_root_pos}}} + 0.2 \underline{r_t^{\text{root_vel}}}$
 - **ball_vel** → target velocity
 - **ball** ↔ **foot** (stay close)
 - **root** → **ball @ target speed**



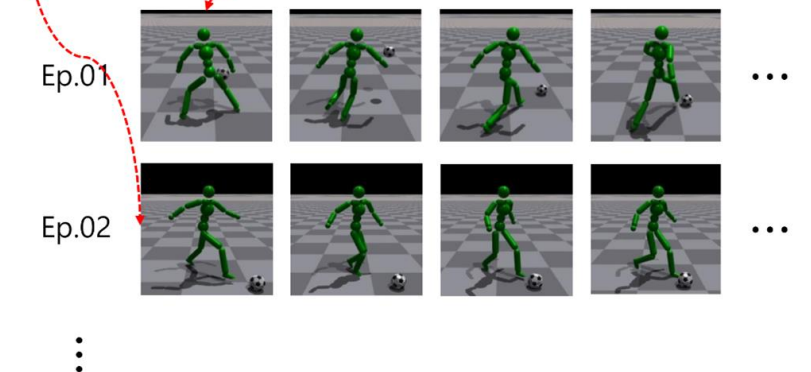
STI: SKILL TRANSITION-BASED INITIALIZATION

- **Quick and smooth skill transitions are crucial in a football.**
- **Problem:** Separately trained skills → transitions are not agile and natural
- **Solution:** **STI** that initialize new episodes from previous skills
- **Method:** Sample from **STI buffer** during training

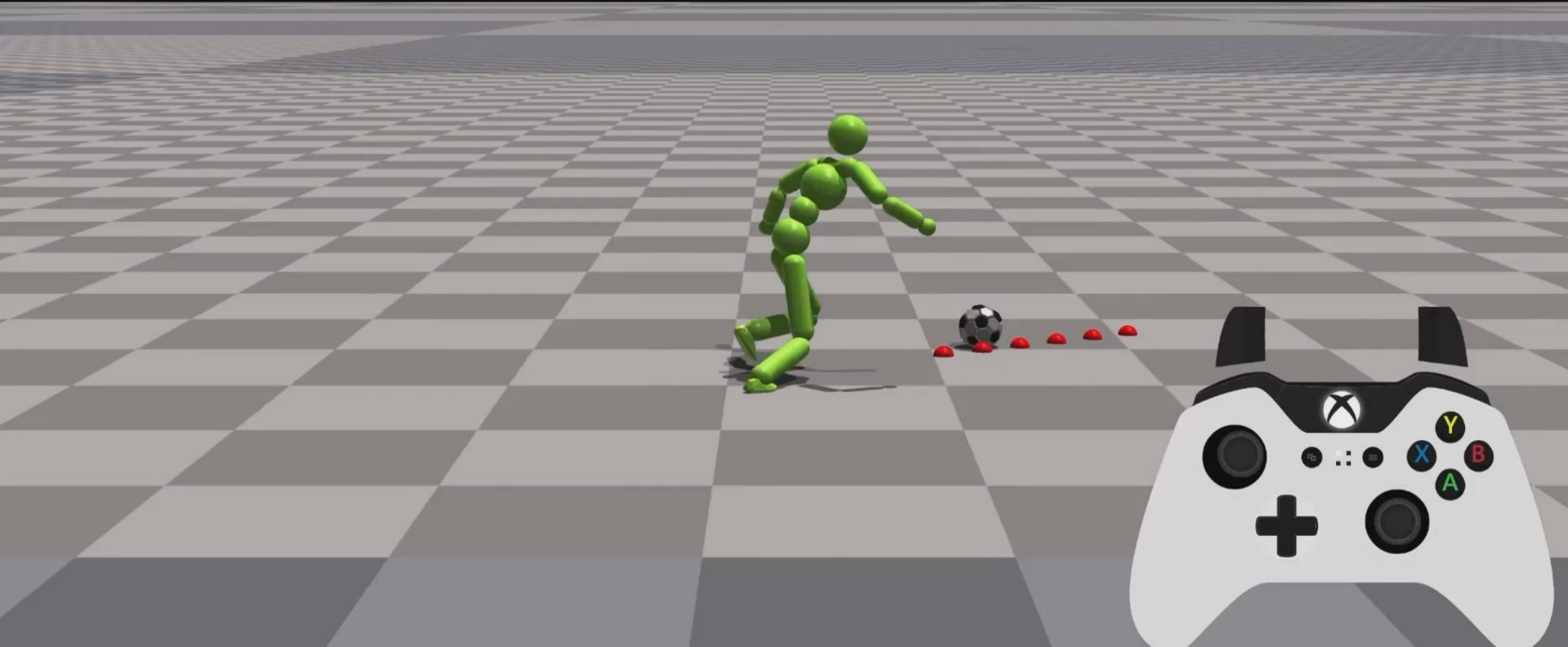
(a) STI Buffer Construction



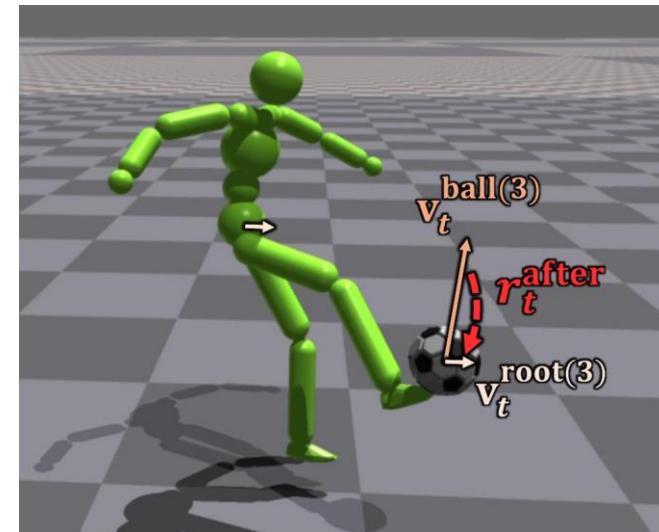
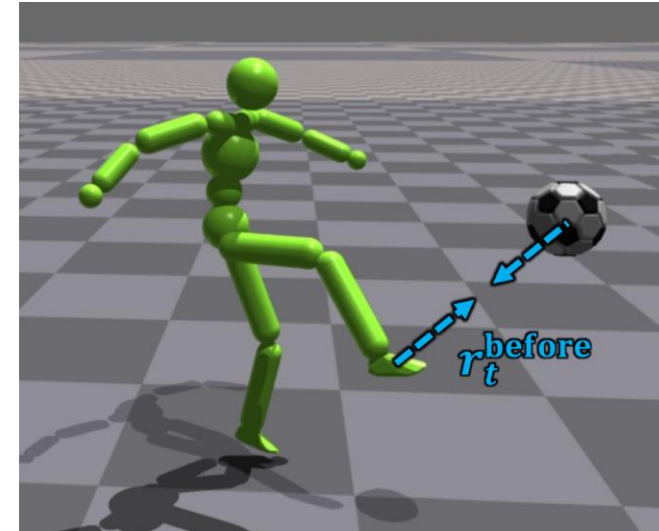
(b) Dribble Policy Training with STI



Target dribble velocity



- **Goal** : Trap the ball with a specified body part
- **Input** : One-hot vector (target body part)
- **Reward** :
$$r_t^{\text{trap}} = \begin{cases} \underline{r_t^{\text{before}}} = \exp\left(-10 \left\| \mathbf{x}_t^{\text{ball}(3)} - \mathbf{x}_t^{\text{body}} \right\|^2\right), & \text{if } t \leq t_c \\ \underline{r_t^{\text{after}}} = \exp\left(-10 \left\| \mathbf{v}_t^{\text{ball}(3)} - \mathbf{v}_t^{\text{root}(3)} \right\|^2\right), & \text{otherwise} \end{cases}$$
 - **Before** : body \rightarrow ball (minimize distance)
 - **After** : $\mathbf{v}_{\text{ball}} \approx \mathbf{v}_{\text{root}}$ (smooth stop)

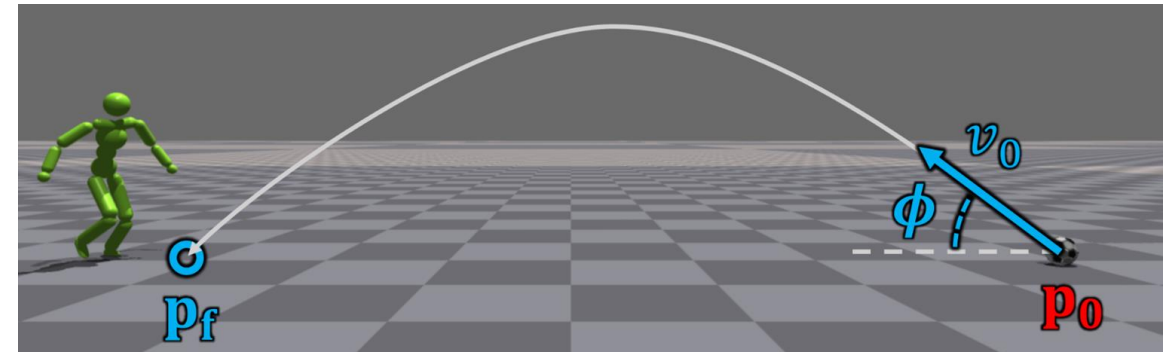


TRAP POLICY: EPISODE INITIALIZATION

- In trap policy training, proper **episode initialization** is important

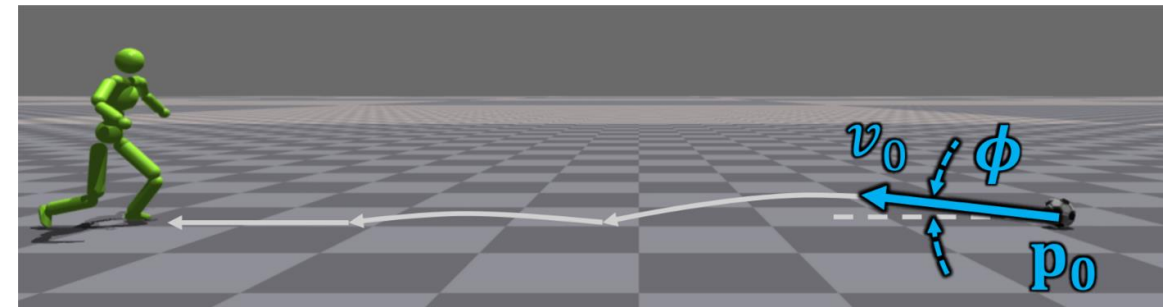
- **Ball (lob):**

- Random: launch angle, speed, landing position
- Computed: initial position ← **from projectile dynamics**



- **Ball (ground):**

- All params (angle, speed, landing, initial) sampled randomly

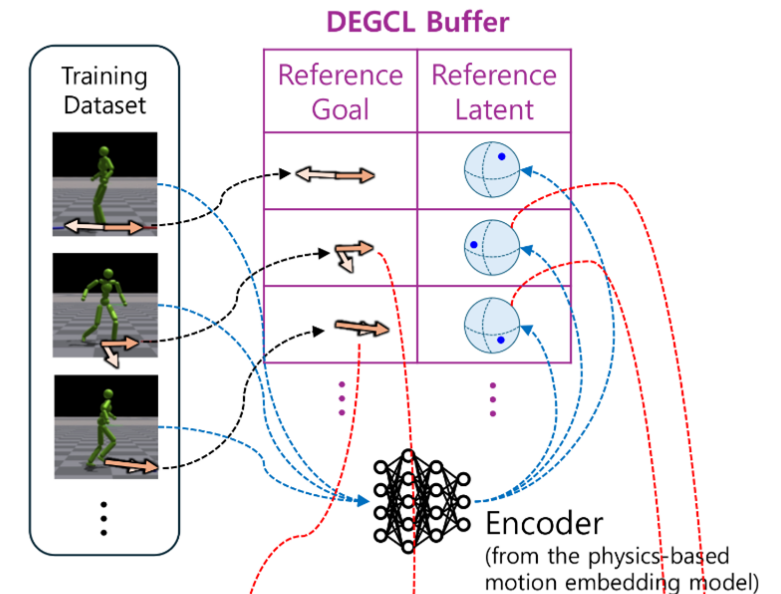


■ Target body part

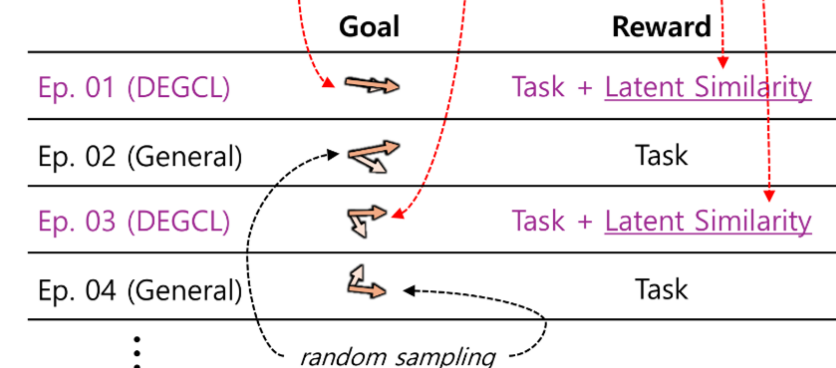


- **Goal** : Control move velocity, facing direction
- **DEGCL** : Data Embedded Goal-Conditioned Latent Guidance
→ Guides the policy using motion data's latent goal-action relationship
- **Why?**
 - Task-only training may miss diverse motions (e.g., sideways/backward walk)
- **How?**
 - **Sample (Reference Goal, Reference Latent)** from motion dataset
 - Train policy to align latent z output with reference latent z
 - Reward: task + latent similarity (only in DEGCL episodes)

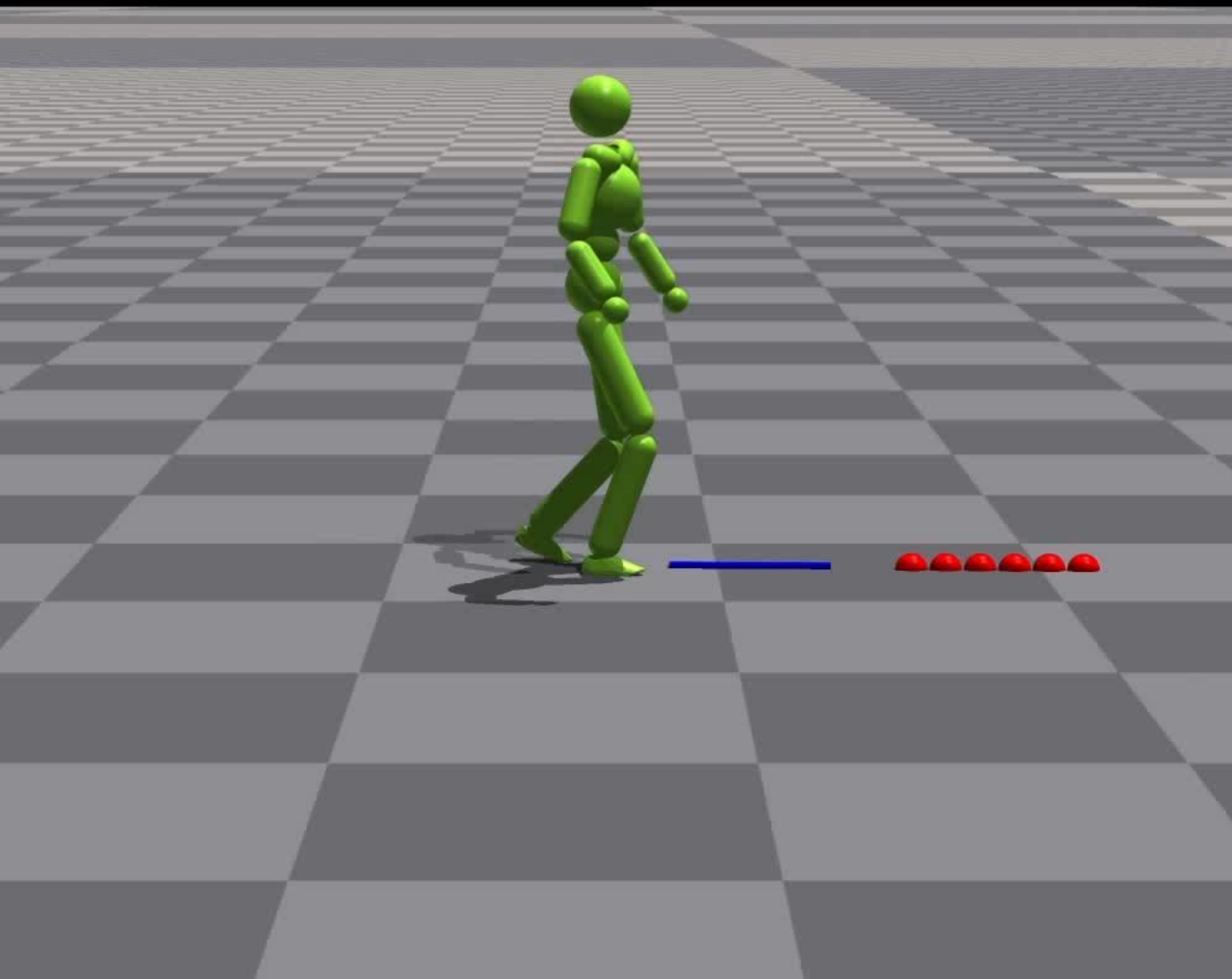
(a) DEGCL Buffer Construction



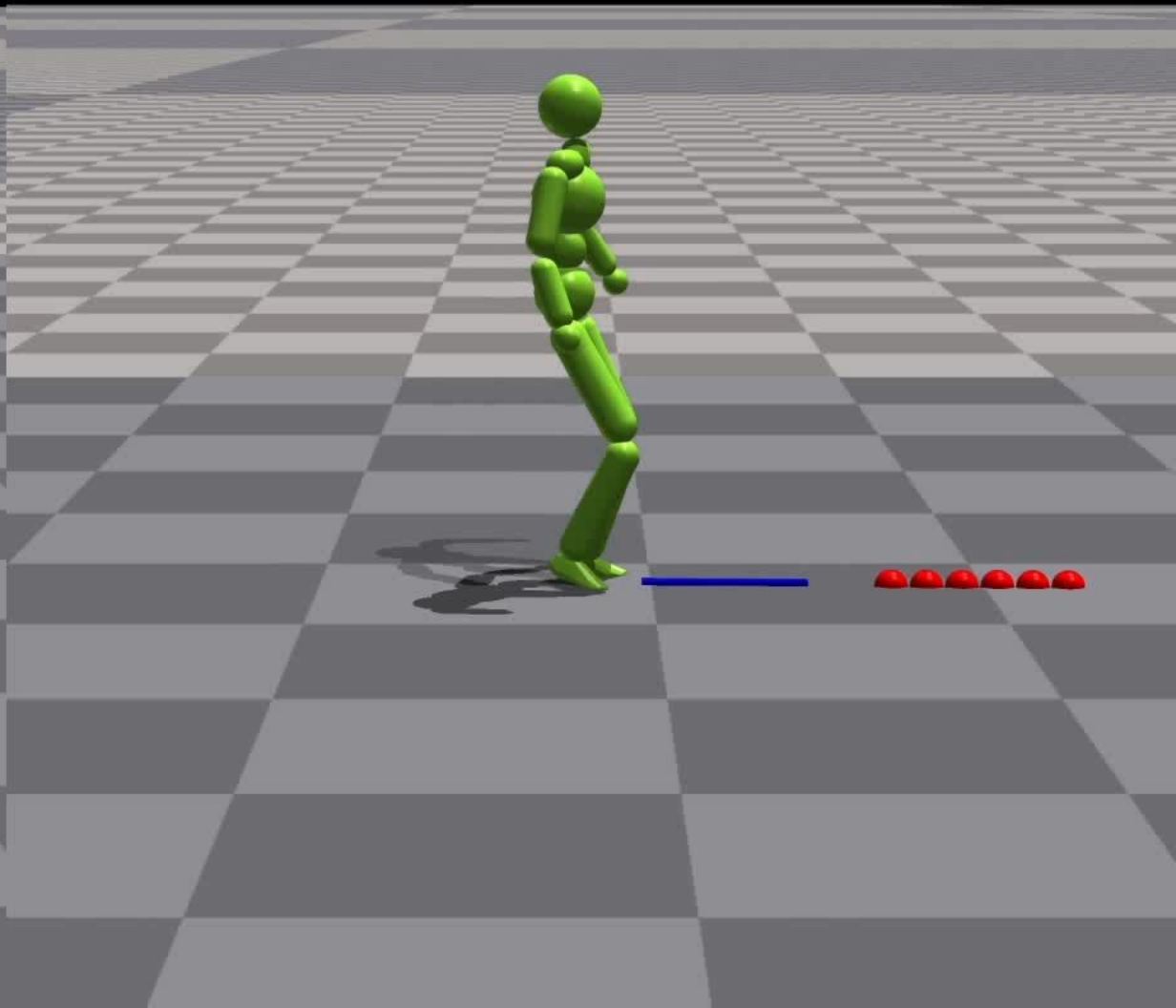
(b) Move Policy Training using DEGCL / General Episodes



Ours



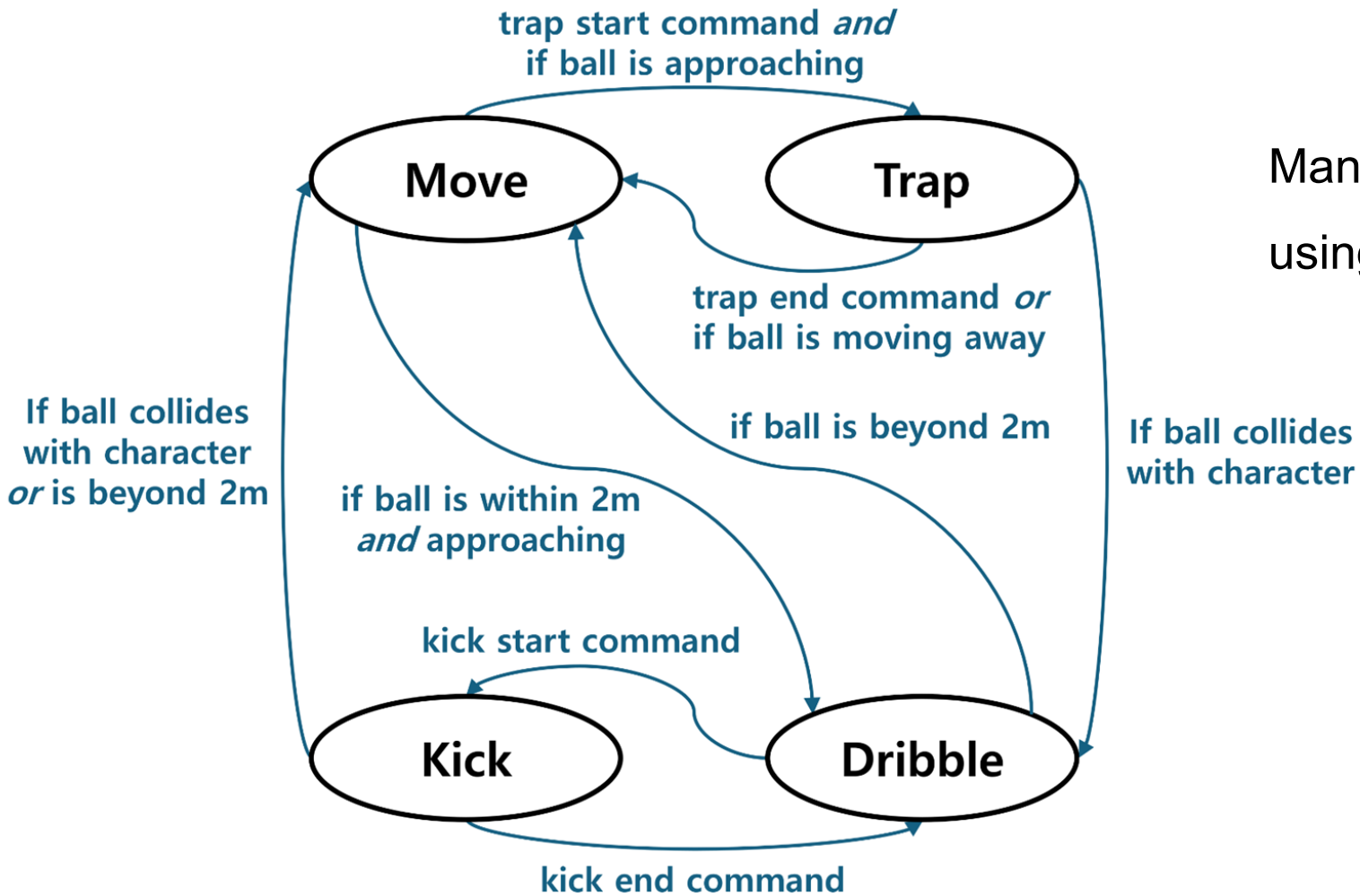
w/o DEGCL



- **Goal** : Kick with target velocity
- **Input** : Target kick velocity (3D)
- **Reward** : $r_t^{\text{kick}} = \exp\left(-\left(\frac{\|\hat{\mathbf{v}}_t^{\text{kick}} - \mathbf{v}_t^{\text{ball}(3)}\|}{\|\hat{\mathbf{v}}_t^{\text{kick}}\| + \epsilon}\right)^2\right)$
 - **ball_vel** \approx **target velocity (direction + speed)**
 - evaluated briefly after contact

Expected ball trajectory

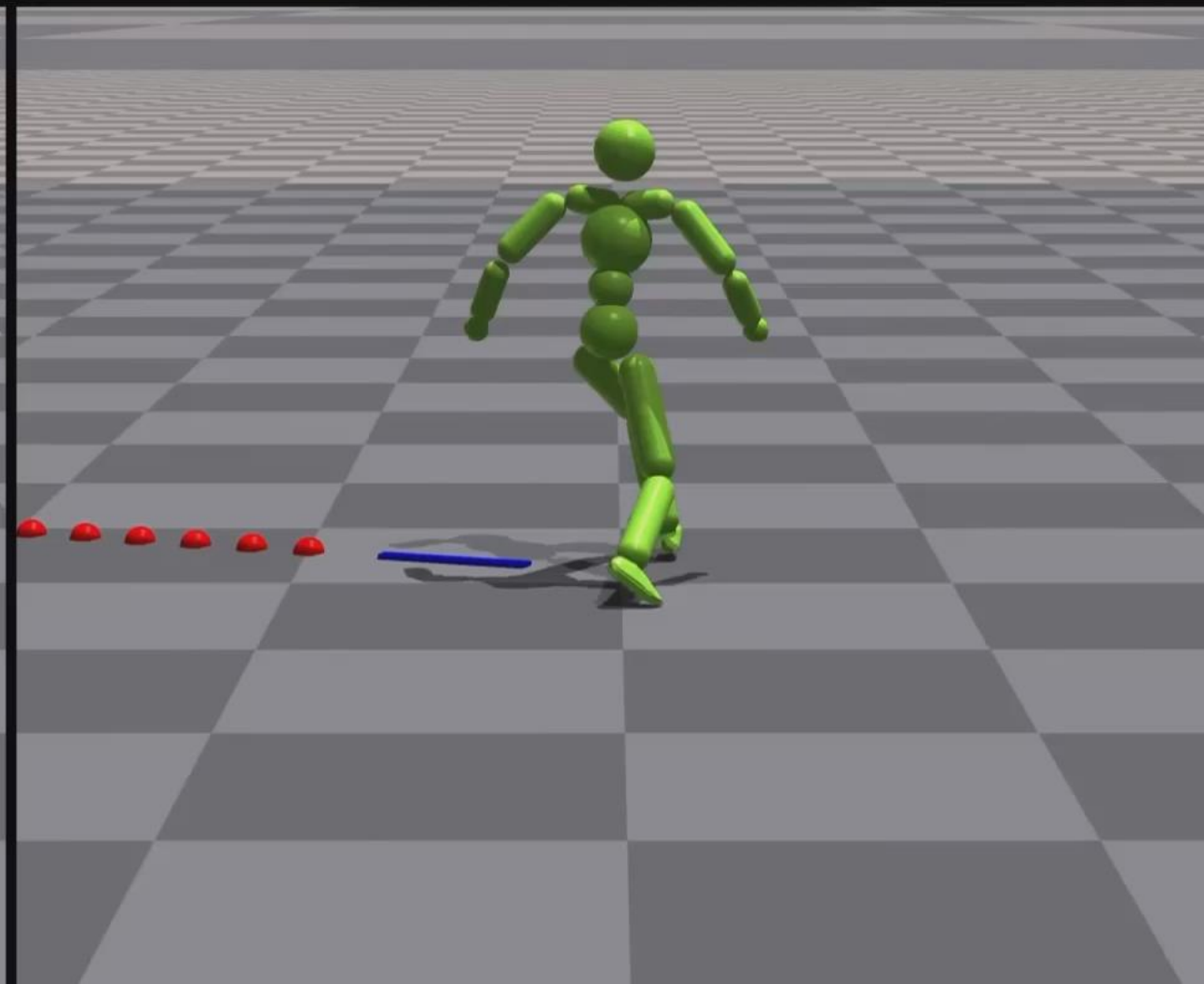
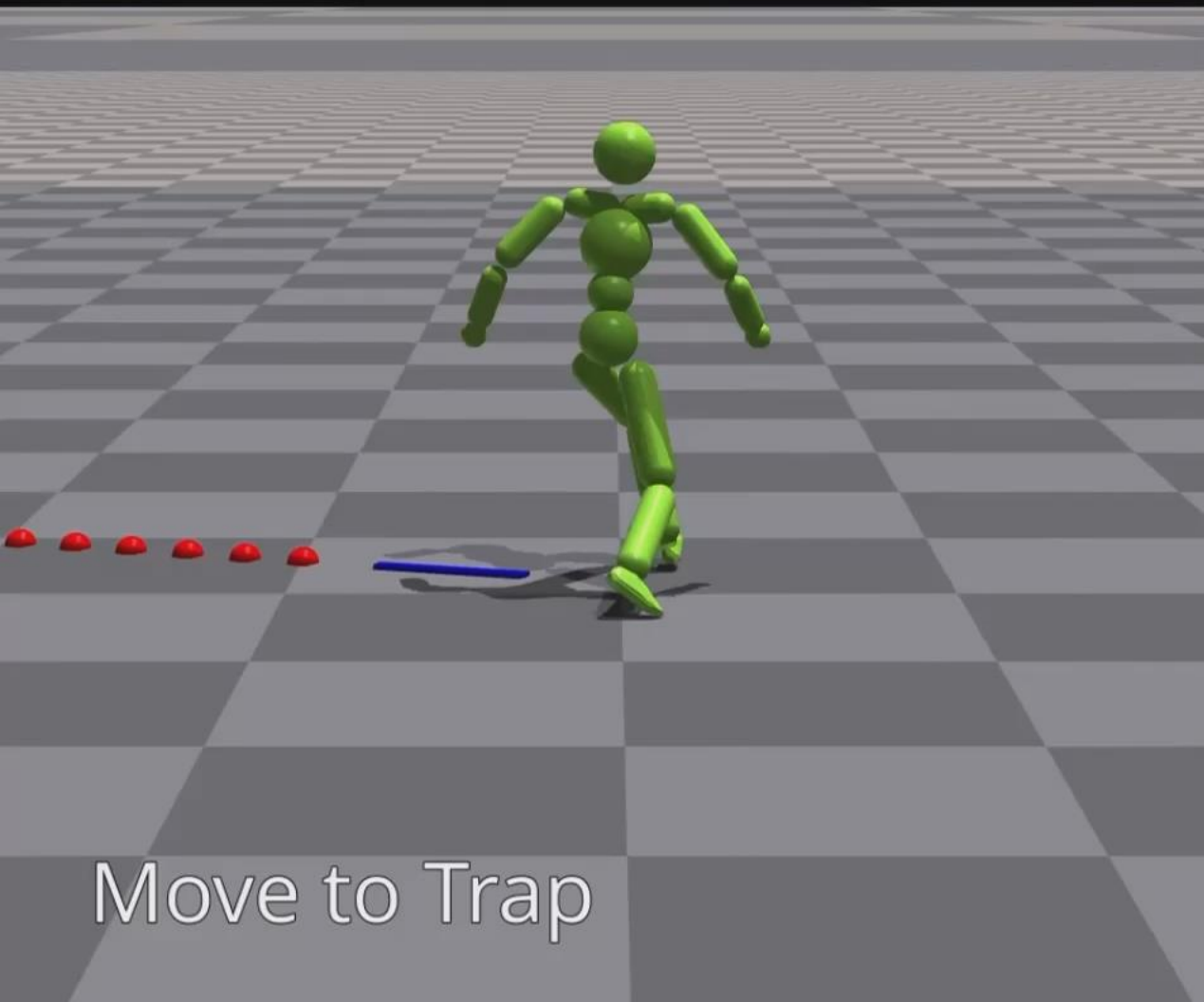




Manages transitions between learned skills using predefined rules.

Trap-Ours

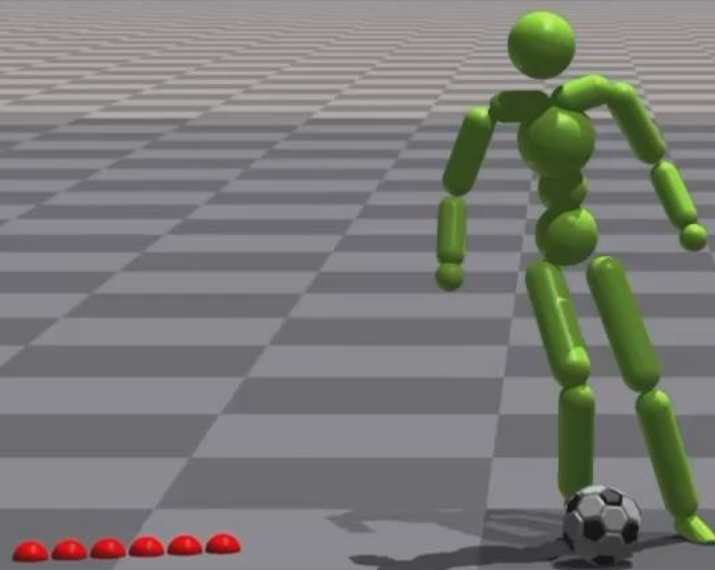
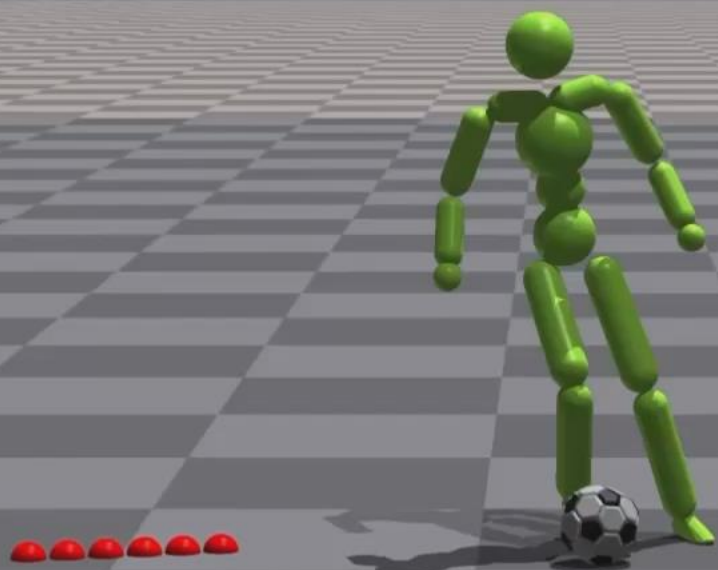
Trap-w/o STI



Move to Trap

Kick-Ours

Kick-w/o STI



Dribble to Kick

- **Defined dedicated performance metrics** for each **individual skill** (Trap, Dribble, Move, Kick) and for **skill transitions** (e.g., Dribble→Kick).
 - Example: **Trap skill** - **Trapping Success Rate (TSR)**, **Handball Ratio in Trapping Success (HRTS)**, **Relative Ball Speed Post-Trap (RBSPT)**

	TSR(%)↑	HRTS(%)↓	RBSPT(m/s)↓
Trap-w/o r_t^{before}	28.6	5.1	4.75
Trap-w/o r_t^{after}	74.2	9.3	4.43
Trap-w/o ProjectileInit	21.1	5.2	5.22
Trap-w/o HandArmET	77.1	20.7	3.94
Trap-Ours	78.3	5.6	3.69

Trap skill evaluation

	KSR(%)↑	TTK(s)↓	KDD(°)↓	KSD(m/s)↓
Kick-Ours	100	2.99	16.9	5.81
Kick-w/o STI	16.95	3.35	37.41	7.21

Dribble→Kick evaluation

→ **Comprehensive evaluation of both skills and transitions validates our approach**

PhysicsFC: Learning User-Controlled Skills for a Physics-Based Football Player Controller

Minsu Kim, Eunho Jung, Yoonsang Lee*

Hanyang University

- Move
- Tran
- Dribble
- Kick

Come to our table to play the game!

