



Simulating Fast-Movements with Mixture-of-Expert models

An Interactive Boxing Controller

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Agenda



Motivation

Mortal Kombat X:
Limited punch actions



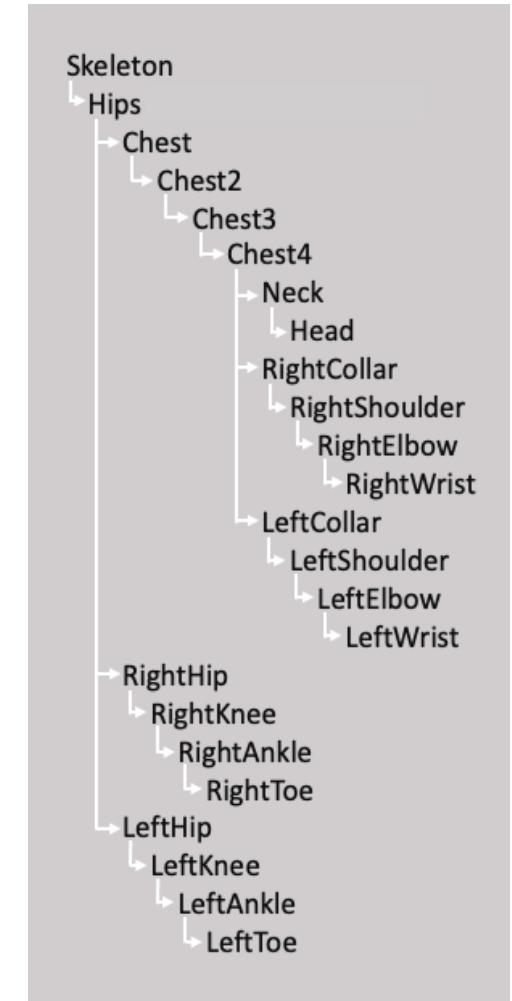
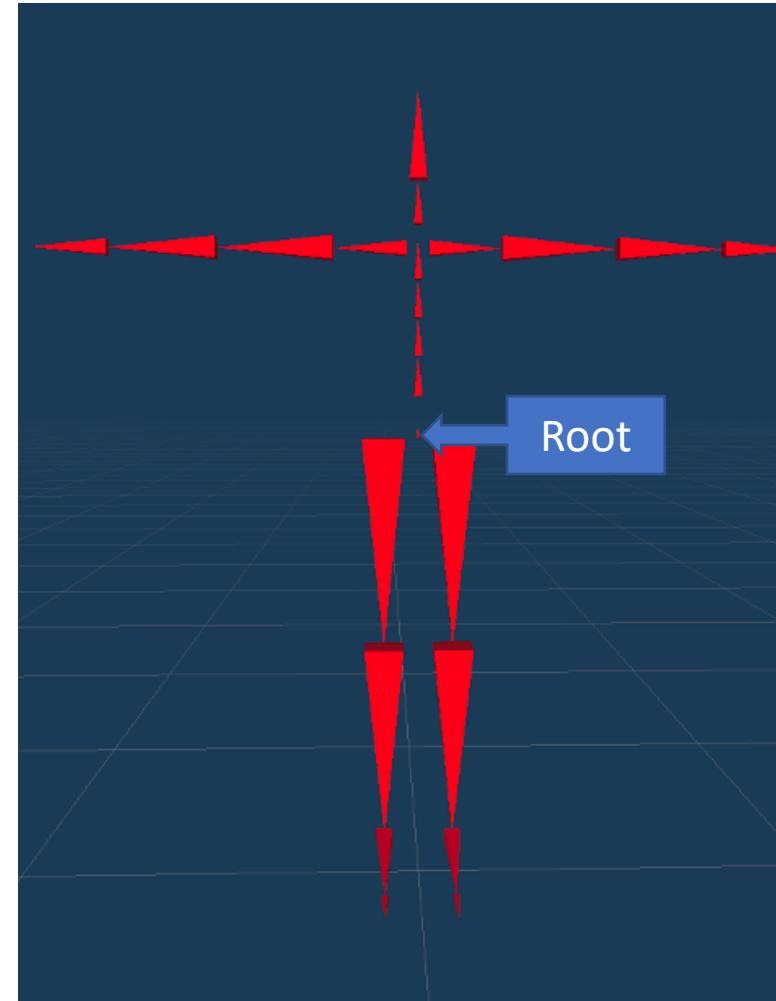
GTA 5:
Punch missing



Synthesise targeted punches
from boxing!

What is motion synthesis?

- ❑ Virtual World
- ❑ Virtual skeleton
 - Hierarchy
 - Parent of all → Root joint
- ❑ Manipulate skeleton



Use-cases

- Computer games
- Animated movies



Approaches

- Kinematics
 - Use position, velocity, acceleration
- Dynamics
 - Apply rules of Physics

Challenges in boxing synthesis

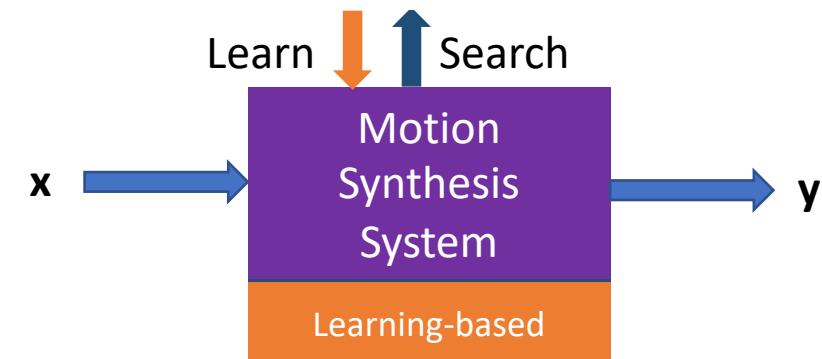
- ❑ Boxing actions are fast
 - ❑ Boxing actions are non-periodic
 - ❑ Targeted punch control
 - Realism
 - Responsiveness
 - ❑ Stepping has distinct style
 - ❑ Dynamic models bring in more complexity
 - ❑ Real-time user interaction
- Boxing specific
- Combo is too complicated!



Use kinematic model first

Data-driven motion synthesis

- ❑ Reference motion data
- ❑ Categorized into:
 - Search-based
 - Learning-based
- ❑ Search-based
 - Database required
 - Scalability issue
- ❑ Learning-based
 - Function replaces database
 - No search required

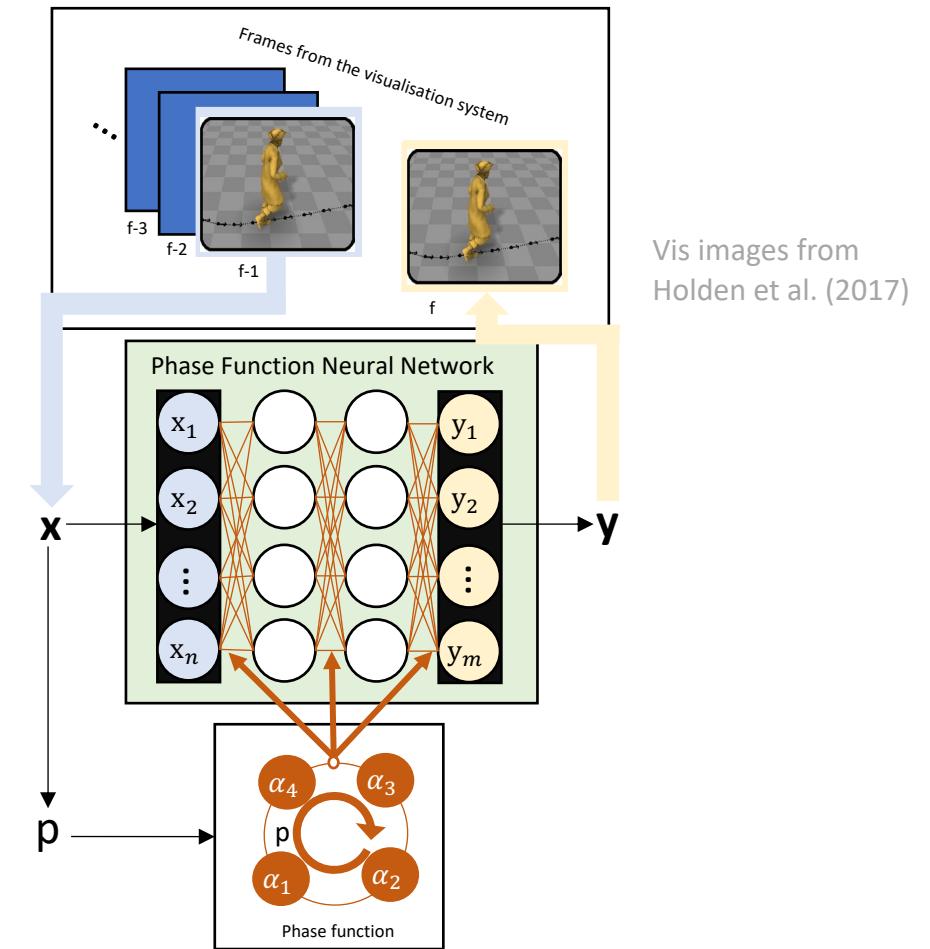


Use learning-based approach

Phase Function Neural Network (PFNN)

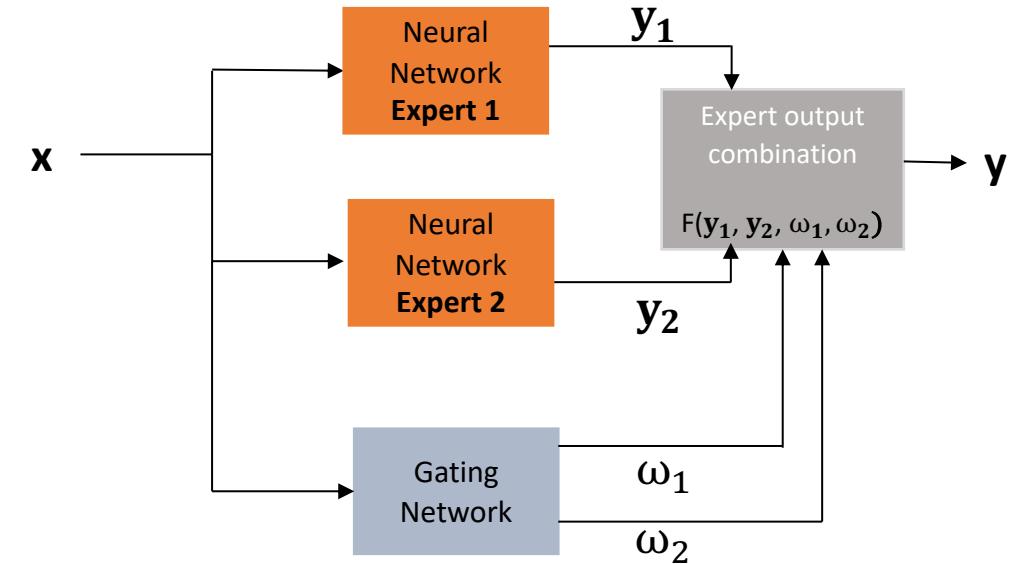
(Holden et al. 2017)

- ❑ Locomotion tasks
- ❑ Change network weights dynamically
- ❑ Fixed phase function



Mixture of Experts (MoE)

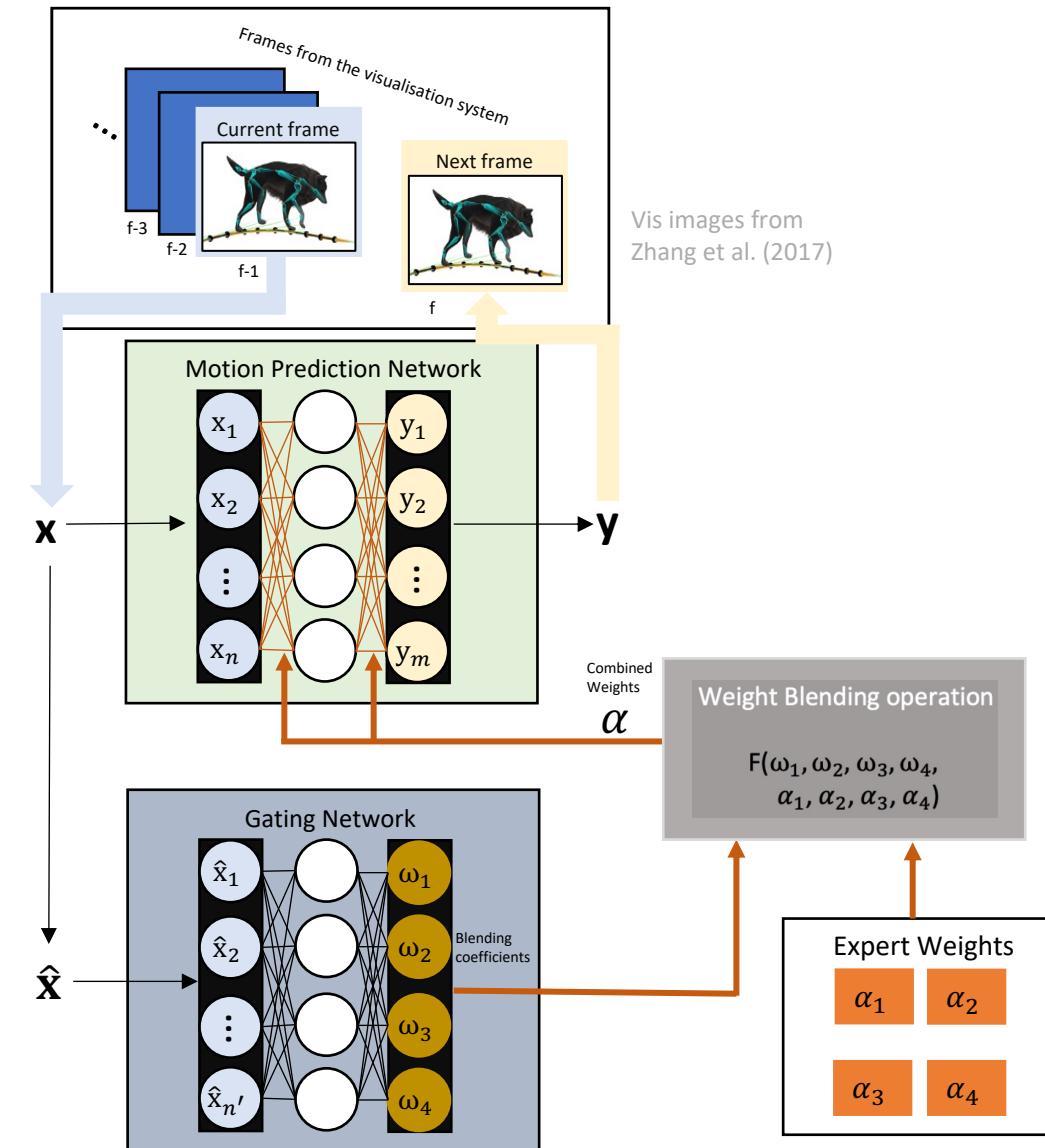
- Zhang et al. (2017)
 - Quadruped control
 - Gait labelling hard
 - PFNN not sufficient
- Mixture of Experts
 - Developed by Jacobs et al. (1991)
 - Neural network experts
 - Gating network
 - Each expert learns one action



Mode Adaptive Neural Network (MANN)

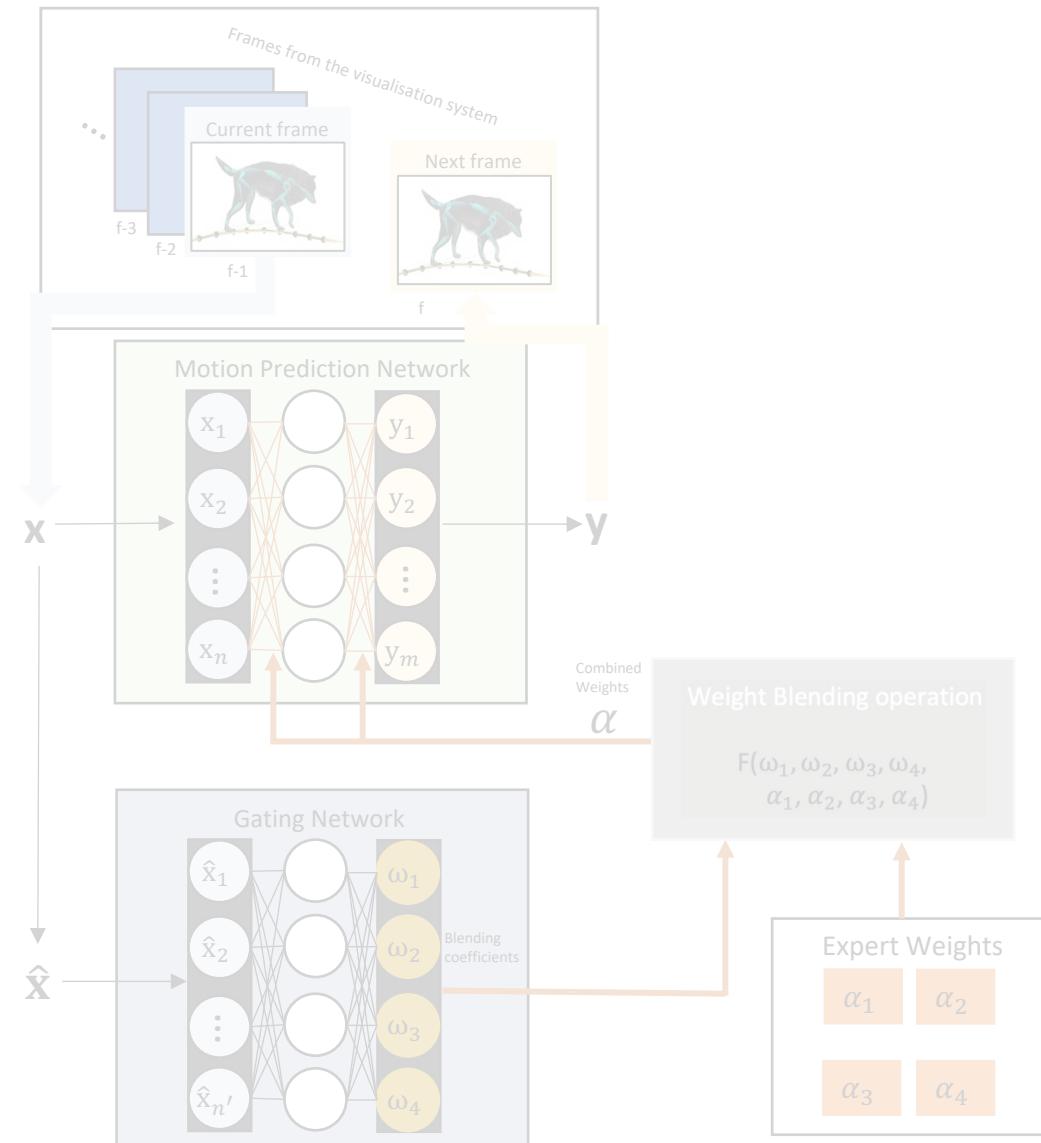
(Zhang et al. 2017)

- ❑ PFNN → Change network weights dynamically
- ❑ Mixture of Experts → Have multiple experts
- ❑ MANN
 - Motion Prediction Network
 - Gating Network
 - Set of Expert weights!



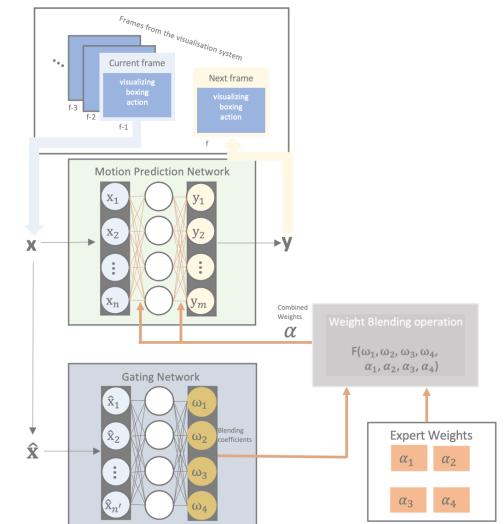
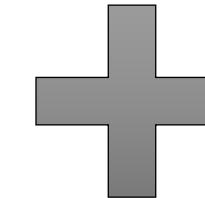
Subsequent MoE models

- Starke et al. 2019
 - Humanoid locomotion
 - Interaction with objects
- Starke et al. 2020
 - One-on-one basketball
 - Interaction with opponent
- Starke et al. 2021
 - Mixed martial arts
 - Punching and kicking



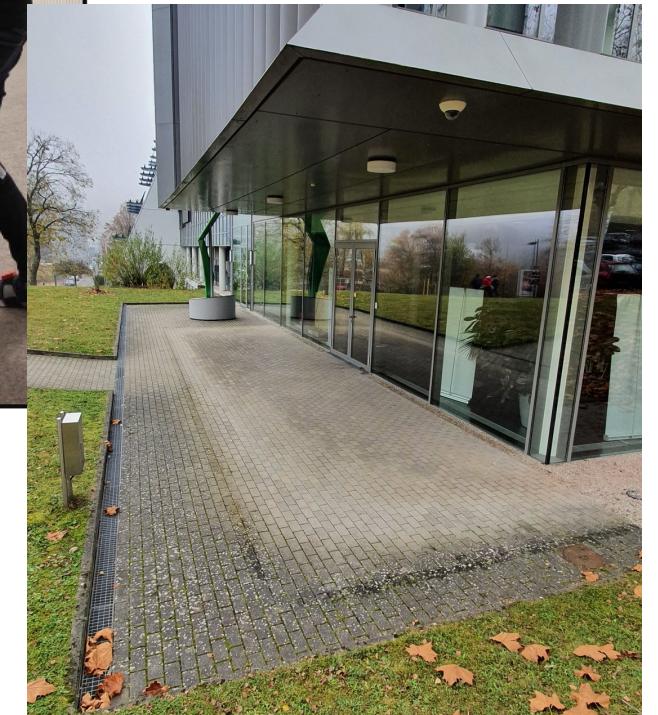
MoE models for boxing?

- Boxing actions are non-periodic
 - Like jumping (in Zhang et al. (2017))
- Boxing stepping
 - Similar to humanoid locomotion
(Starke et al. (2019, 2020, 2021))
- Additional challenges
 - Targeted punch control
 - Stepping in boxing style



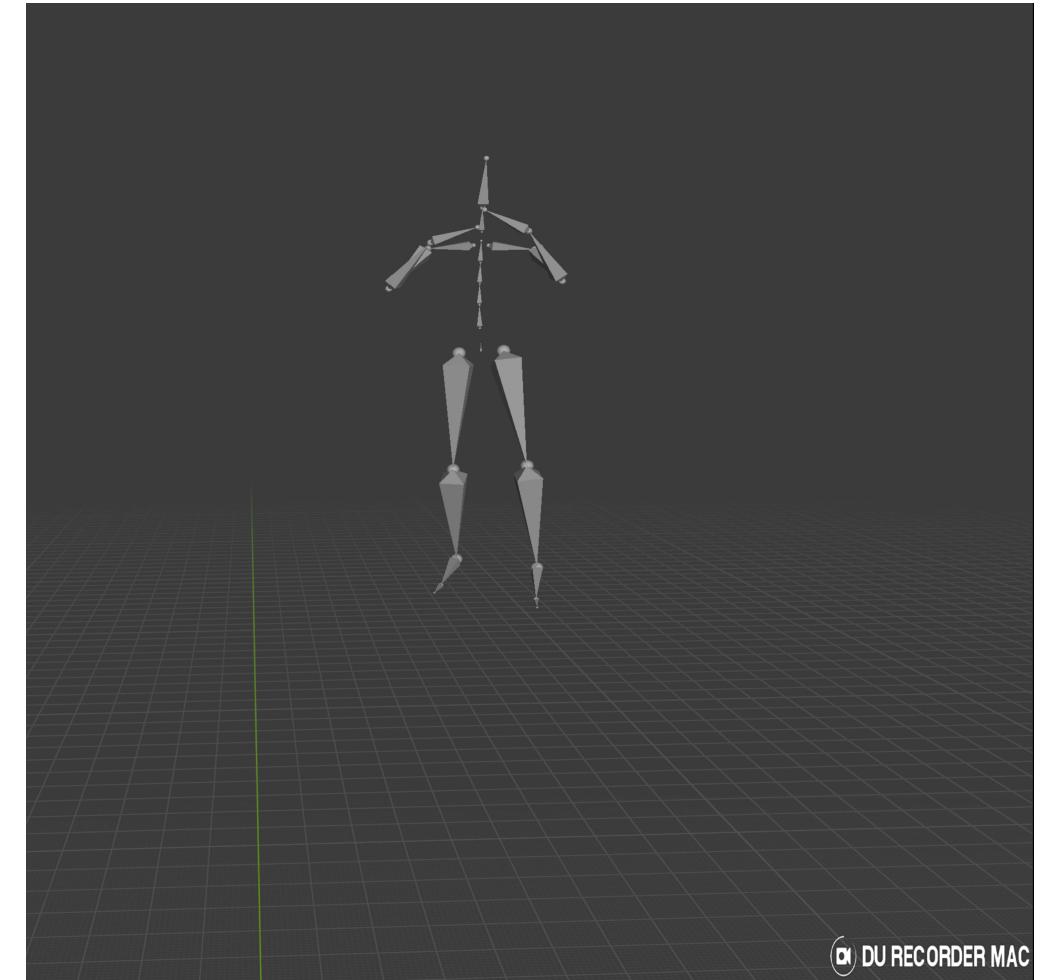
Setup

- ❑ Xsens Awinda Mocap system
 - 60 Hz → 16.7 ms
- ❑ Single actor
 - Intermediate kickboxing exp
- ❑ Capturing region
 - Similar to boxing ring
- ❑ Capturing instructions
 - Shadow boxing
 - Stepping
 - Punching



Cleanup & Result

- ❑ Cleanup
 - Removing unnecessary data
 - Fixing error from sensor slippage
 - Foot skating correction
- ❑ 10 mins of HQ data

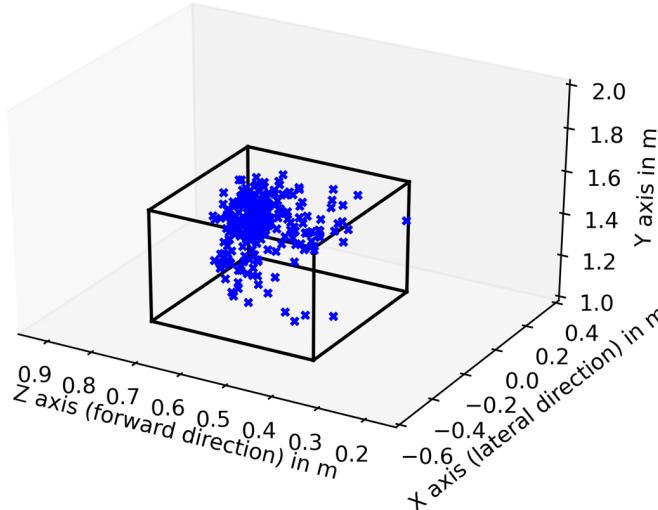


Annotation & Statistics

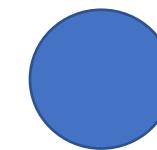
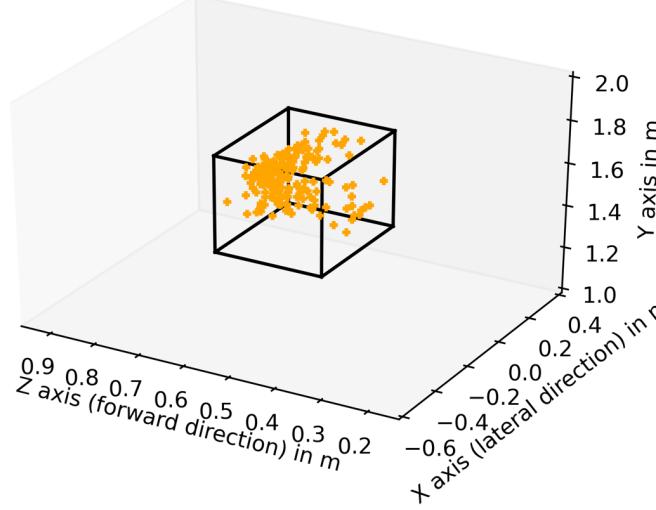
- Automatic punch annotation

- Targets in local space of skeleton
 - Ground projected root at O
 - Looking at +Z axis
 - Root transformation

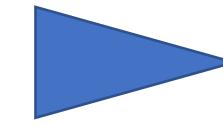
Dataset left punch targets



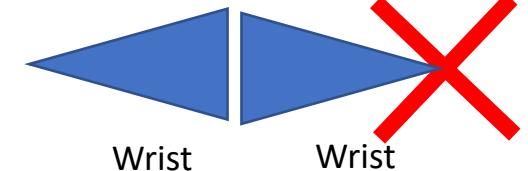
Dataset right punch targets



Shoulder



Wrist



Wrist

Wrist

Punch type	Num punches	Mean duration (frames)
Overall	451	27

Step type	Mean duration (frames)
Overall	20

Motion Prediction Network (MPN)

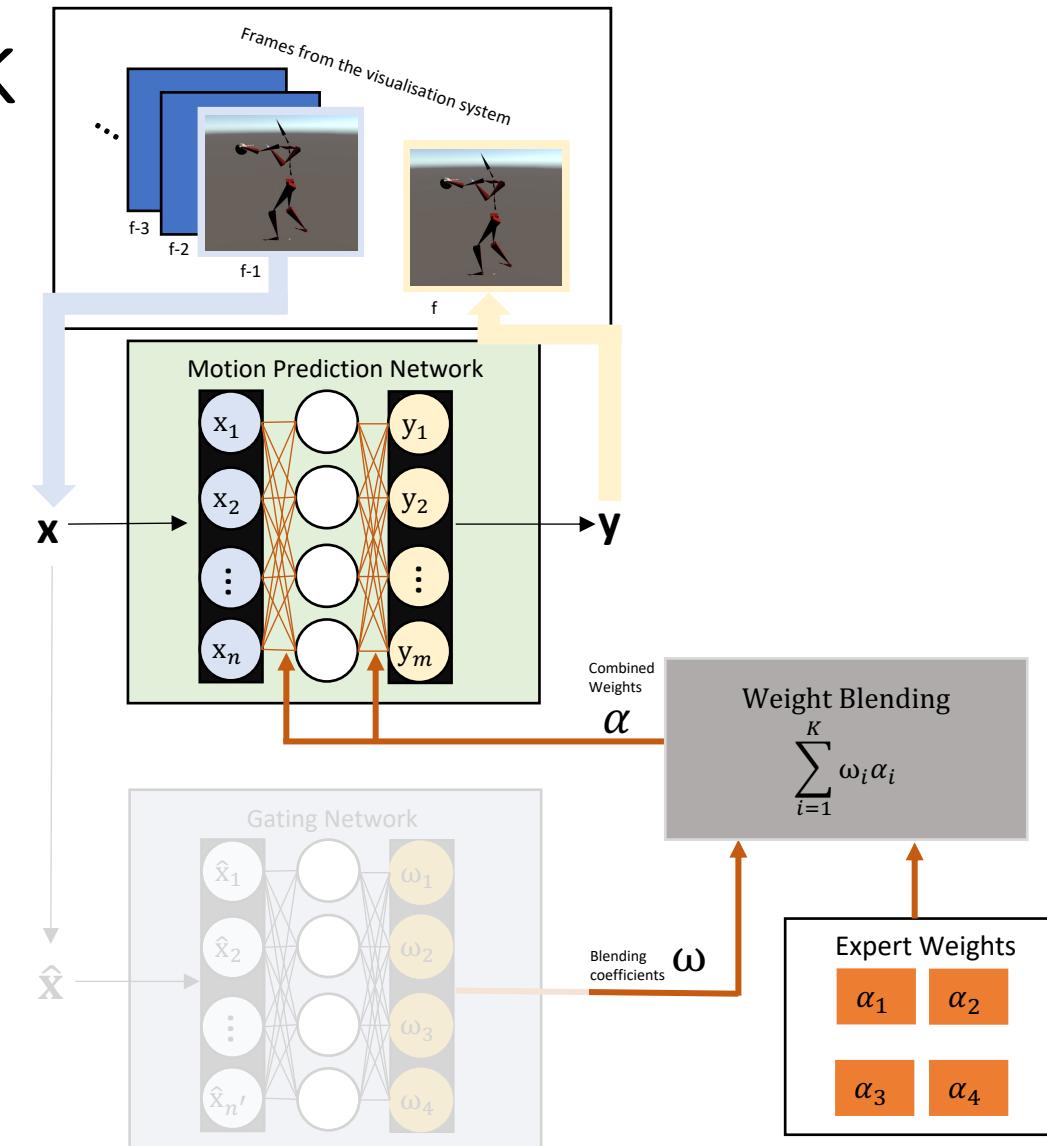
❑ 3 layers

❑ Equation

$$\Theta(\mathbf{x}, \boldsymbol{\alpha}) = \mathbf{W}_2 \text{ELU}(\mathbf{W}_1 \text{ELU}(\mathbf{W}_0 \mathbf{x} + \mathbf{b}_0) + \mathbf{b}_1) + \mathbf{b}_2$$

❑ Weight blending

$$\sum_{i=1}^K \omega_i \alpha_i$$



Gating Network (GN)

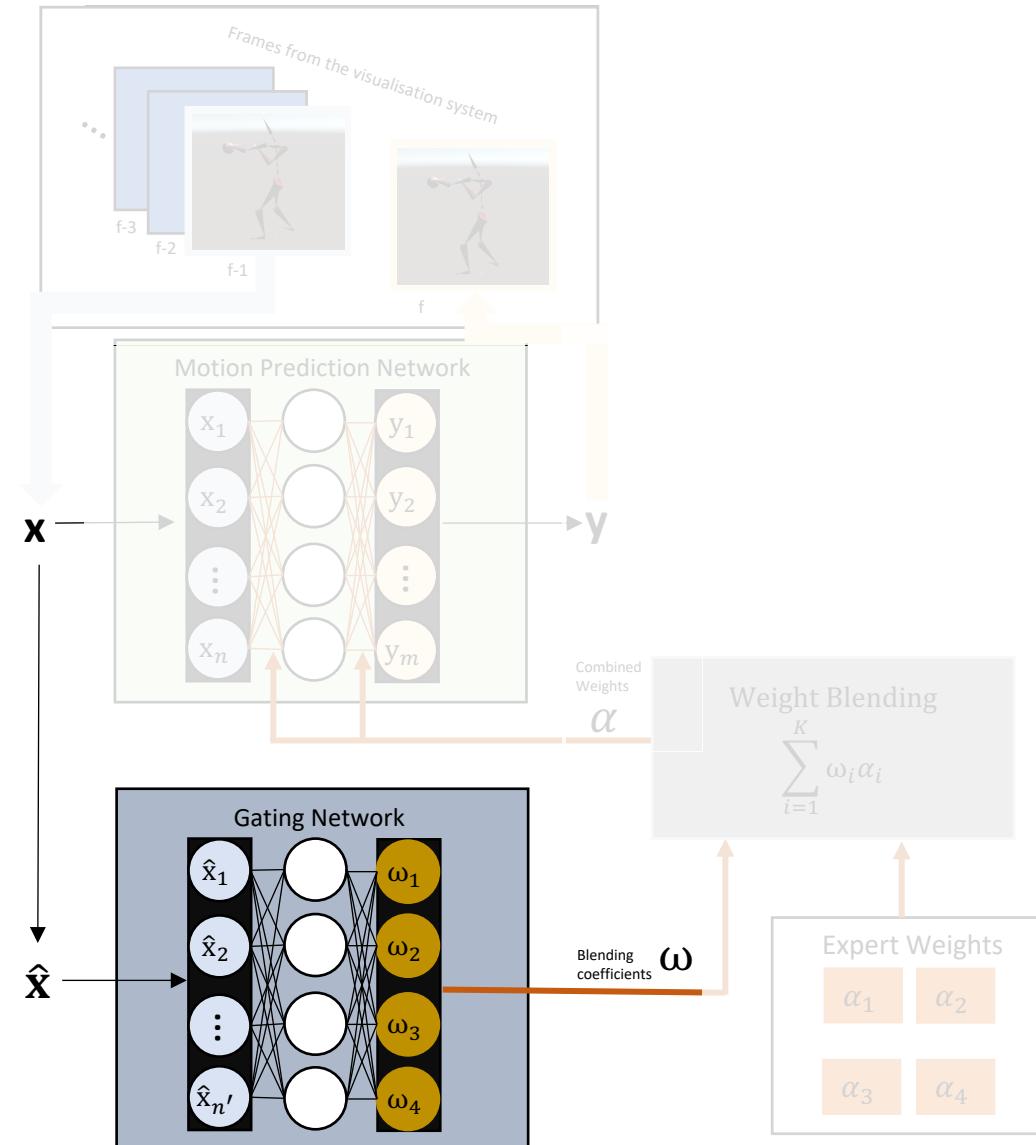
❑ 3 layers

❑ Equation

$$\Omega(\hat{x}, \mu) = \sigma(\hat{W}_2 \text{ELU}(\hat{W}_1 \text{ELU}(\hat{W}_0 \hat{x} + b'_0) + b'_1) + b'_2)$$

❑ Activation function

$$\text{ELU}(z) = \max(z, 0) + \exp(\min(z, 0)) - 1$$



Training Details

- Training data: $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \dots]$ $\hat{\mathbf{X}} = [\hat{\mathbf{x}}_1, \hat{\mathbf{x}}_2, \dots]$
- $\mathbf{Y} = [\mathbf{y}_1, \mathbf{y}_2, \dots]$

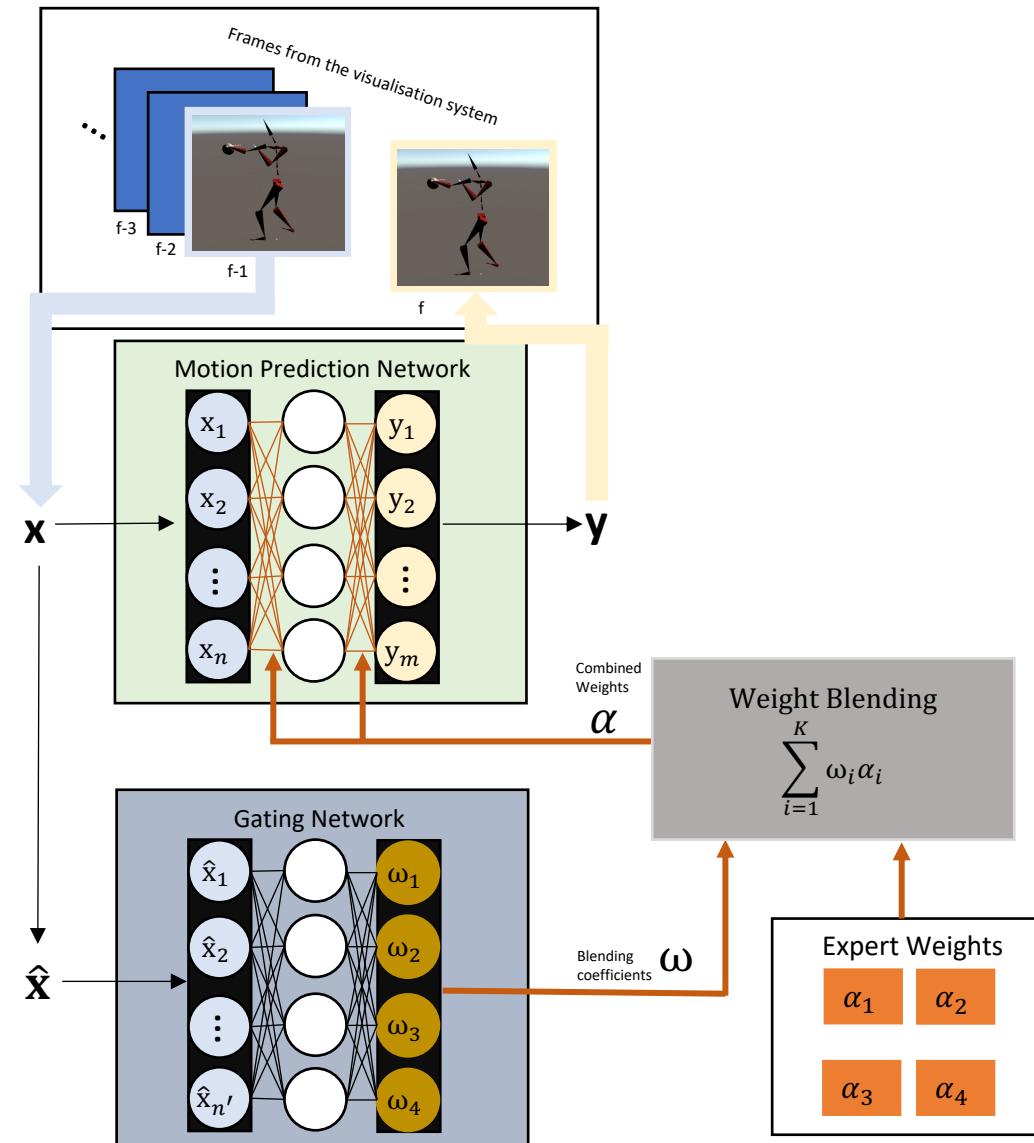
- MSE loss function:

$$Cost(\mathbf{X}, \mathbf{Y}; \boldsymbol{\beta}, \boldsymbol{\mu}) = \|\mathbf{Y} - \Theta(\mathbf{X}, \Omega(\hat{\mathbf{X}}; \boldsymbol{\mu}); \boldsymbol{\beta})\|_2^2$$

- Batch size = 32

- Optimization: Adam with warm restarts

- Training time:
30 – 120 mins on NVIDIA Quadro RTX 8000

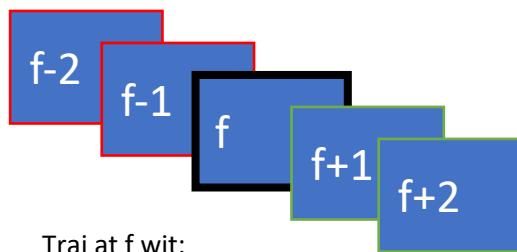


Motion States

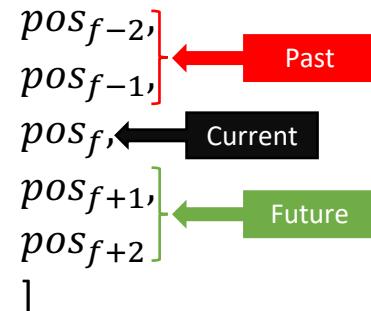
□ Local space of skeleton

- Rotate to face +Z axis
- Place O at ground projected root
- Root transformation

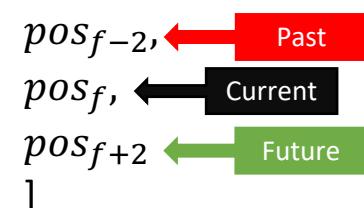
□ Trajectory



$$Tr_{pos} = [$$

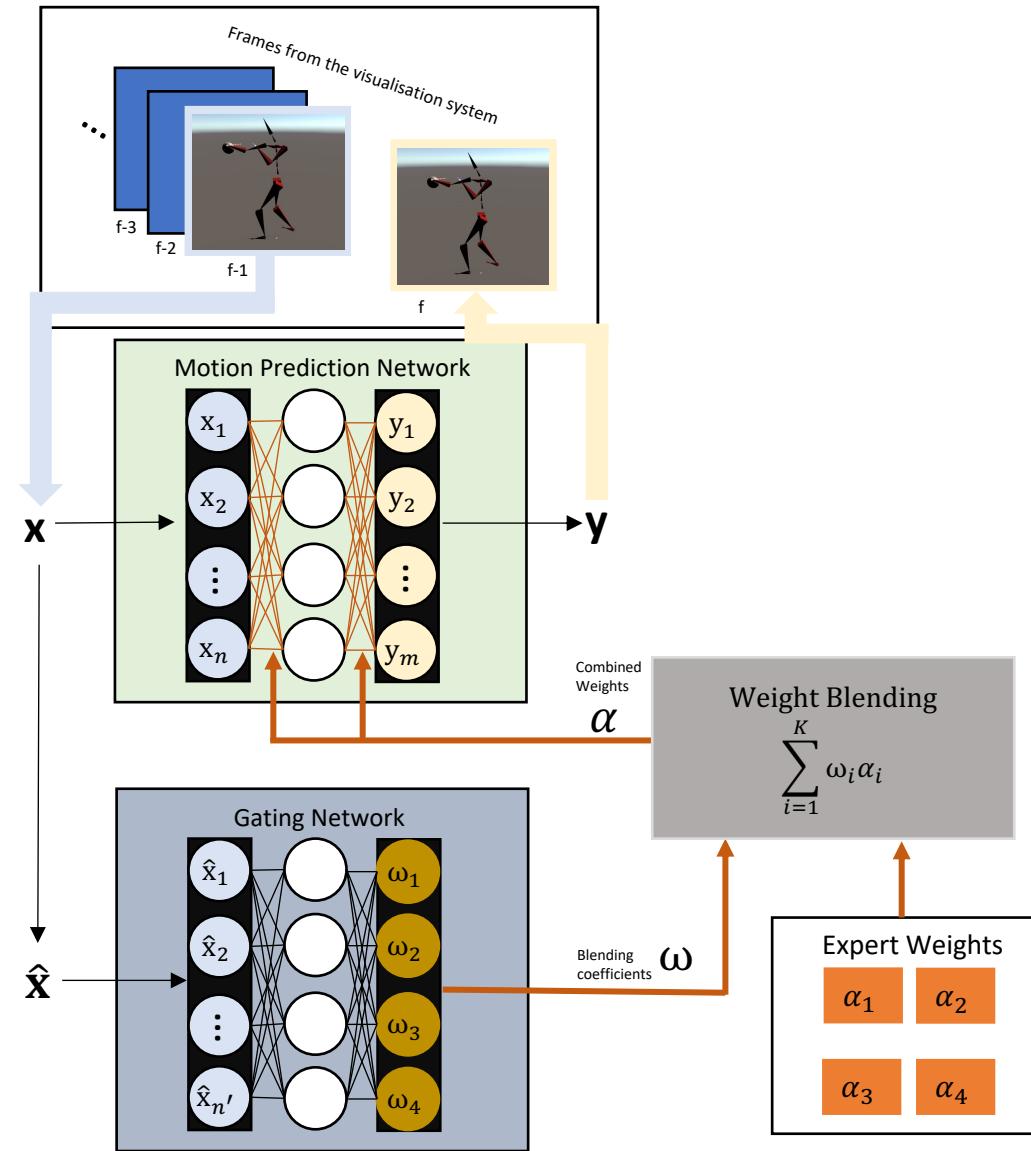


$$Tr_{pos} = [$$



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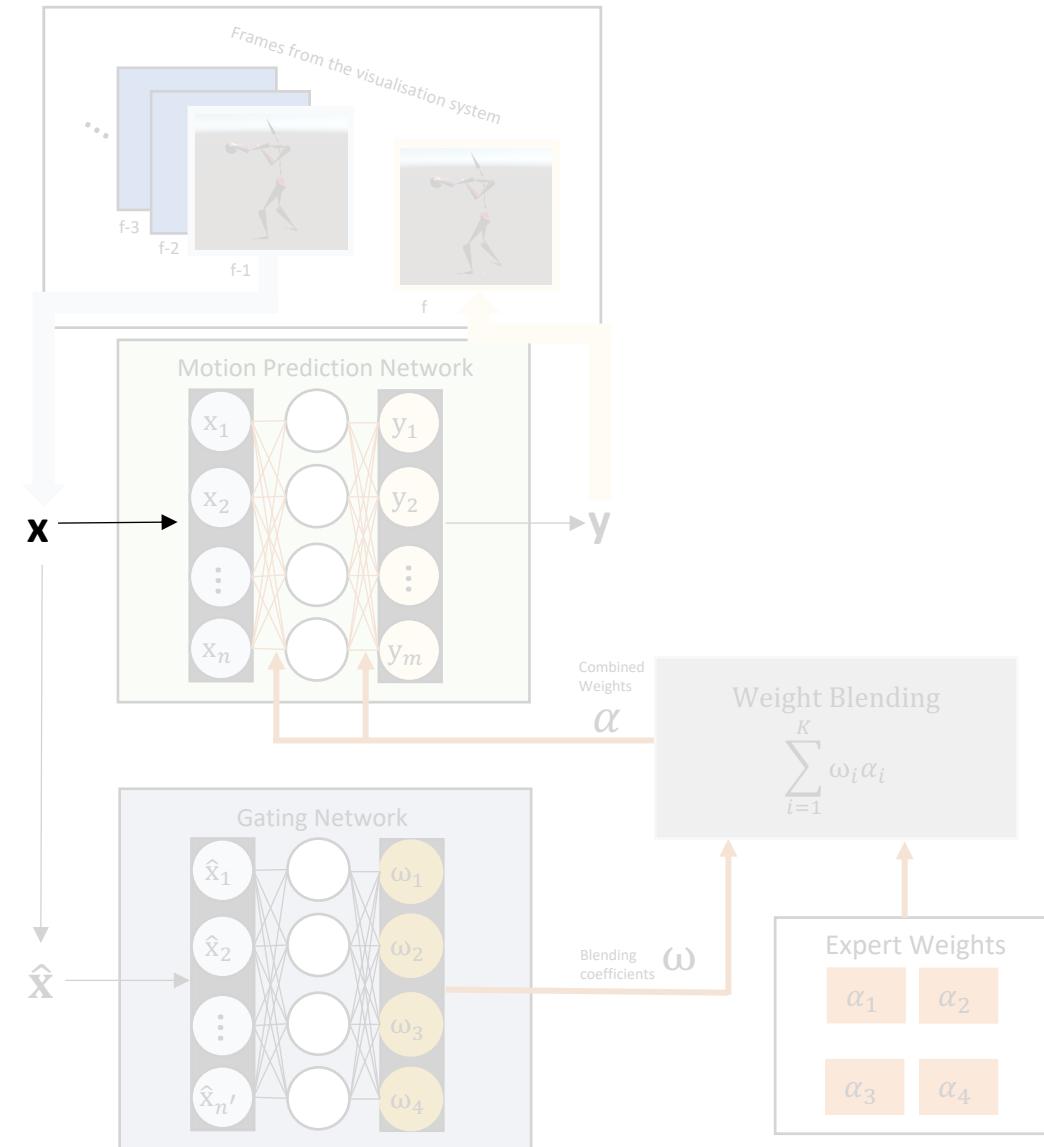
Simulating Fast-Movements with Mixture-of-Expert models



MPN Input

$$\mathbf{x}_f = \{ t_f^{rp}, t_f^{rv}, t_f^{rd}, t_f^{wp}, t_f^{wv}, a_{f-1}^l, a_{f-1}^{pt}, j_{f-1}^p, j_{f-1}^v \} \in \mathbb{R}^n$$

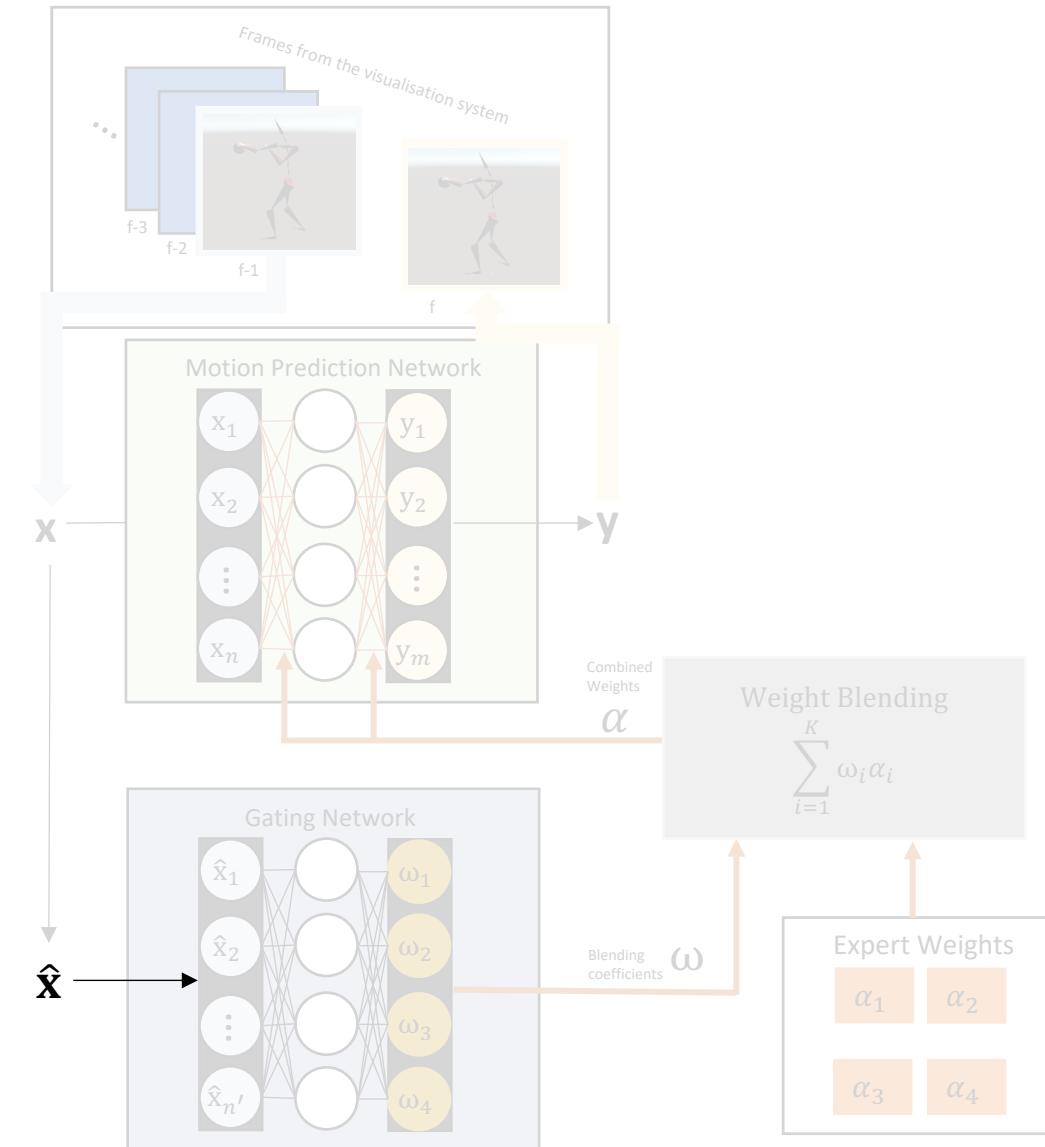
Root trajectory
 Wrist trajectory
 Punch action indicators
 All joints



GN Input

$$\hat{\mathbf{x}}_f = \{ t_f^{rp}, t_f^{rd}, t_f^{wv}, h_{f-1}^{efv}, a_{f-1}^l, b_{f-1}^{efv}, b_{f-1}^{efp} \} \in \mathbb{R}^{n'}$$

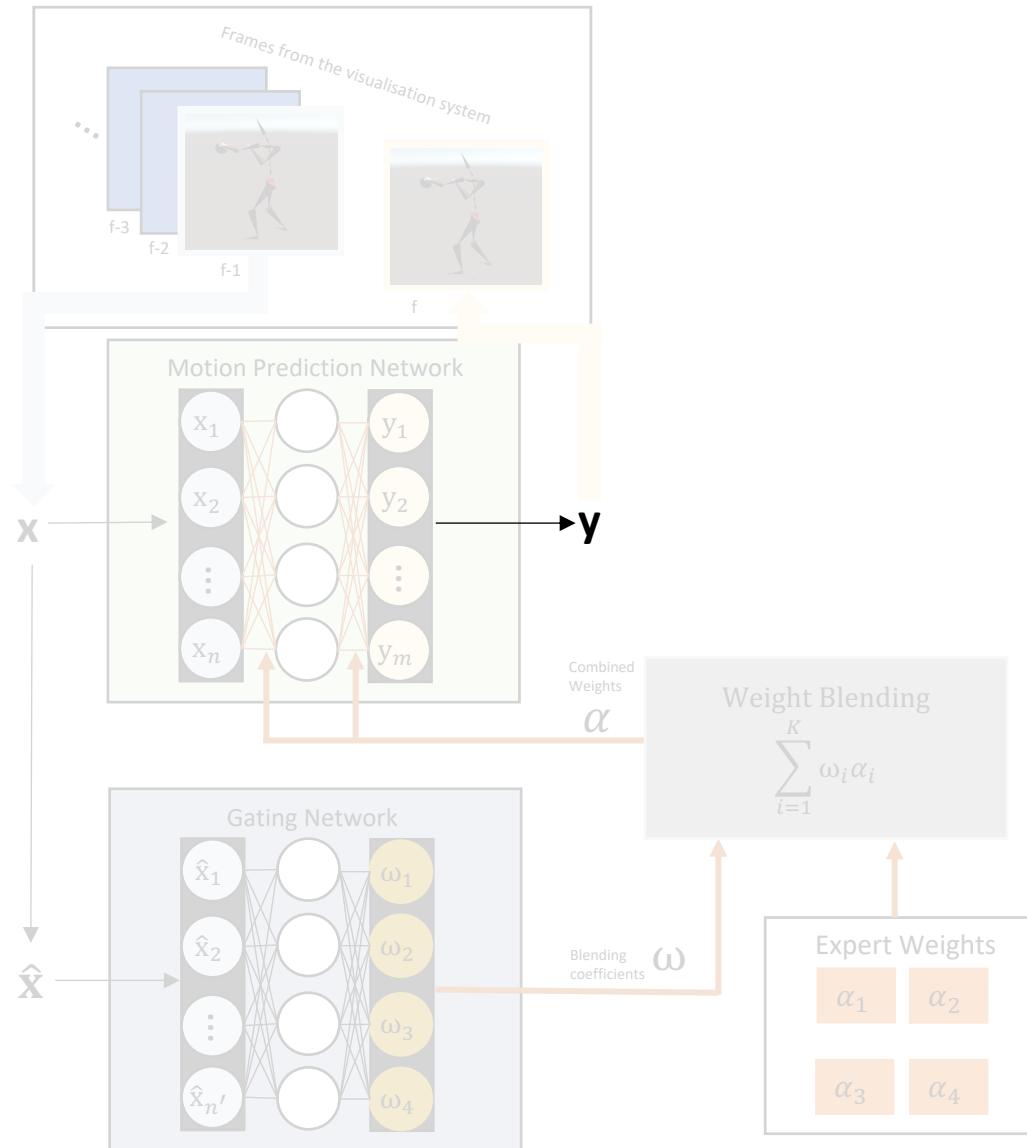
Root trajectory
 Wrist trajectory
 Wrist velocity
 Punch action indicator
 Foot joint



MPN Output

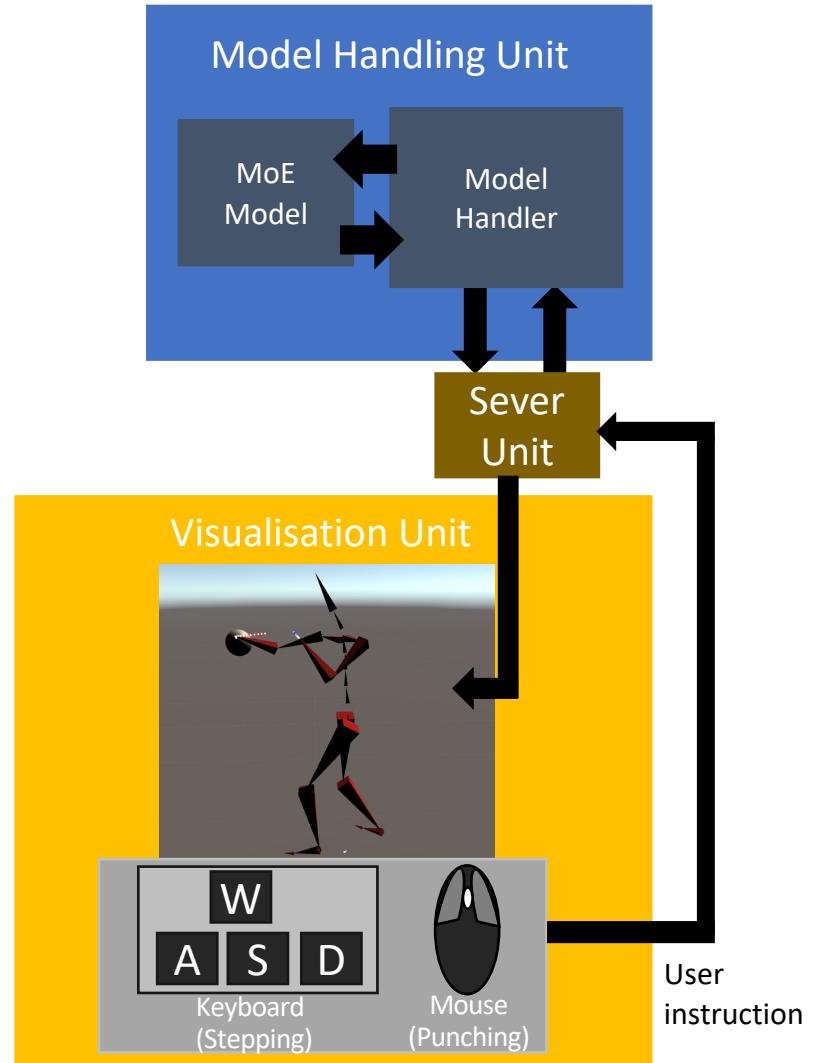
$$\mathbf{y}_f = \{t_{f+1}^{rp}, t_{f+1}^{rv}, t_{f+1}^{rd}, t_{f+1}^{wp}, t_{f+1}^{wv}, a_f^l, a_f^{pt}, q_f^p, q_f^d, b_{f-1}^c, j_f^p, j_f^v\} \in \mathbb{R}^m$$

Root trajectory
 Wrist trajectory
 Punch action indicators
 Root joint
 Foot contact
 All joints



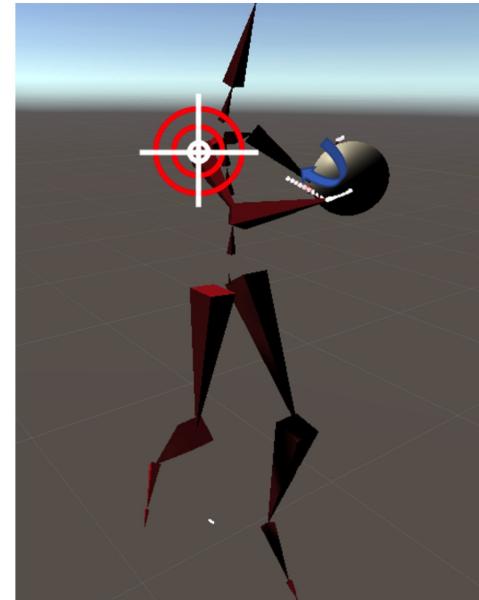
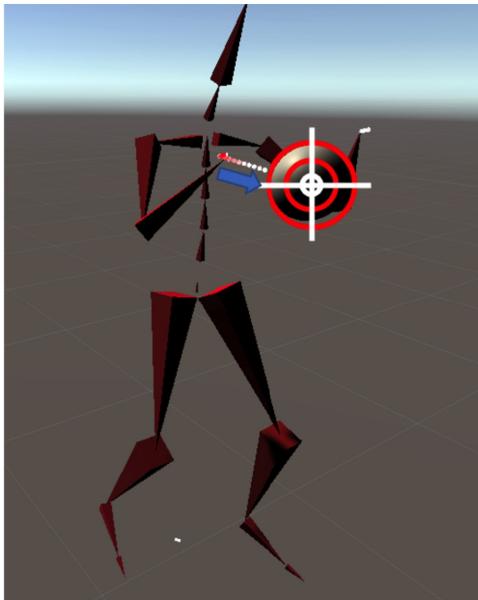
Boxing Controller System

- Visualisation unit
 - User input
 - Motion visualisation
- Model Handling Unit
 - Root transformation
 - Merge user input
- Server Unit

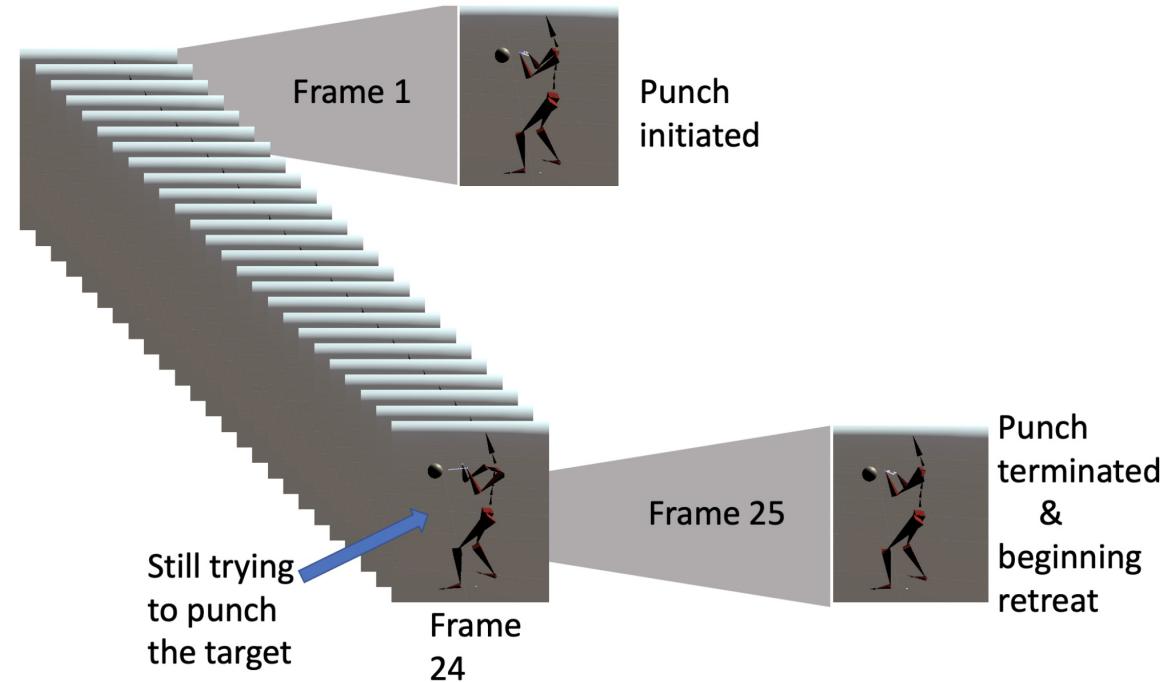


Boxing Controller System

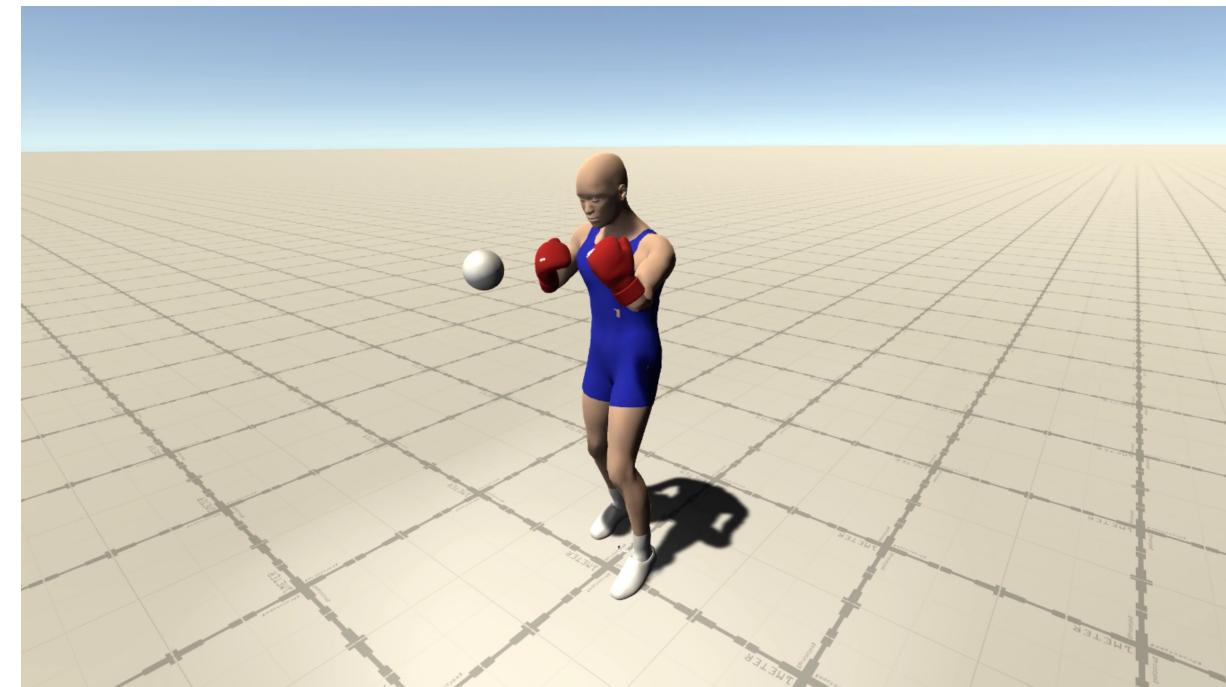
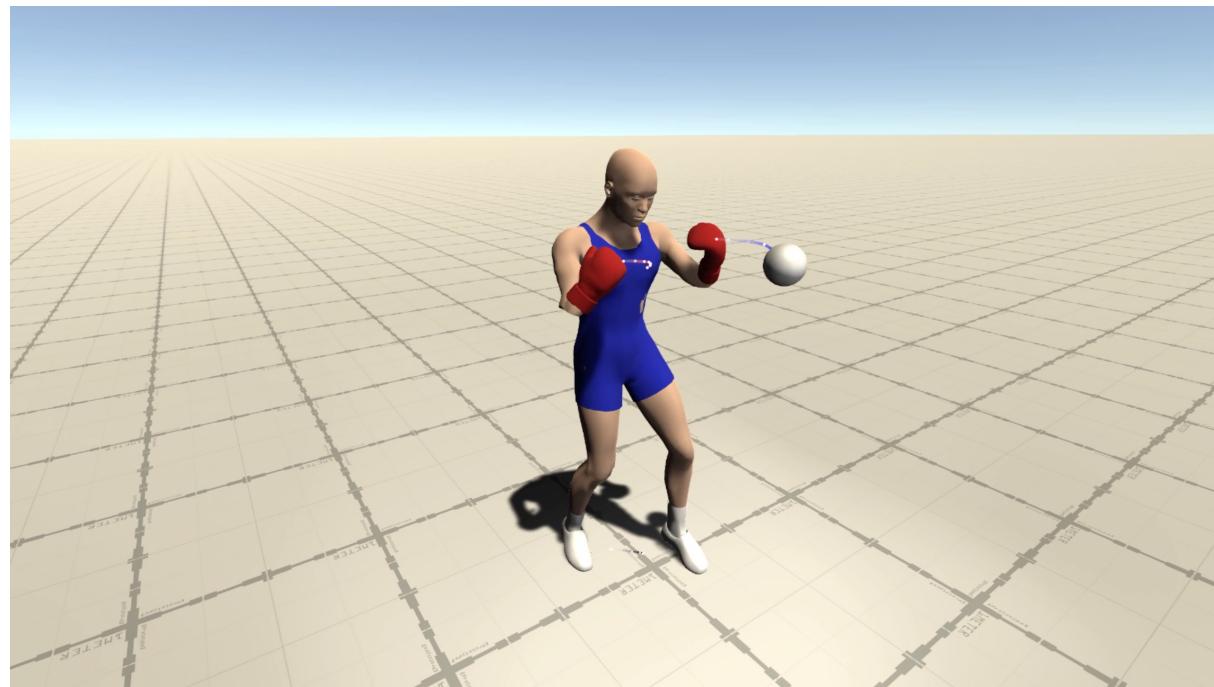
Punch target management



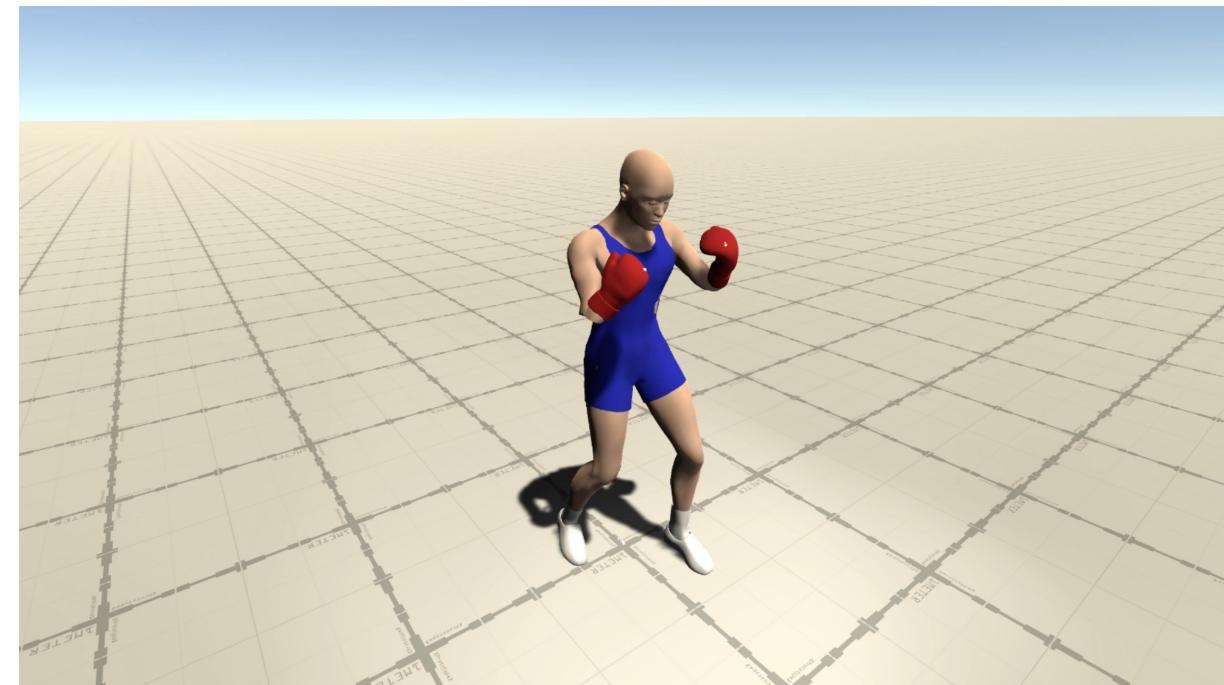
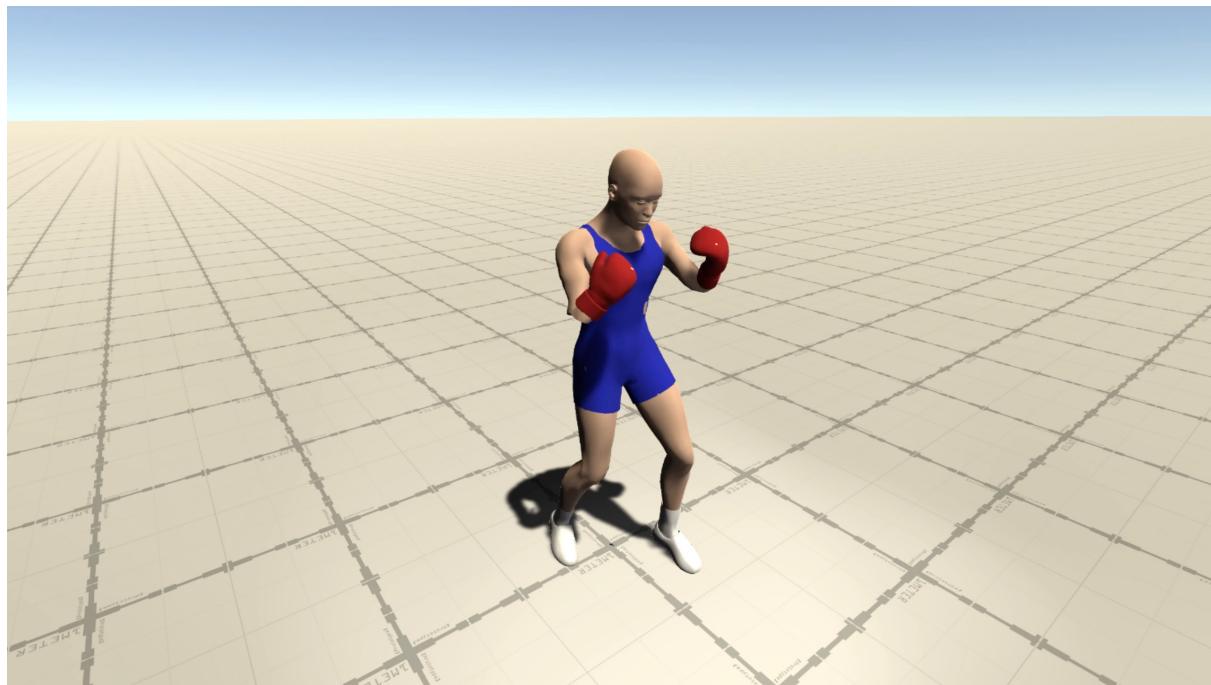
Punch termination on miss



Visualisation: Punching

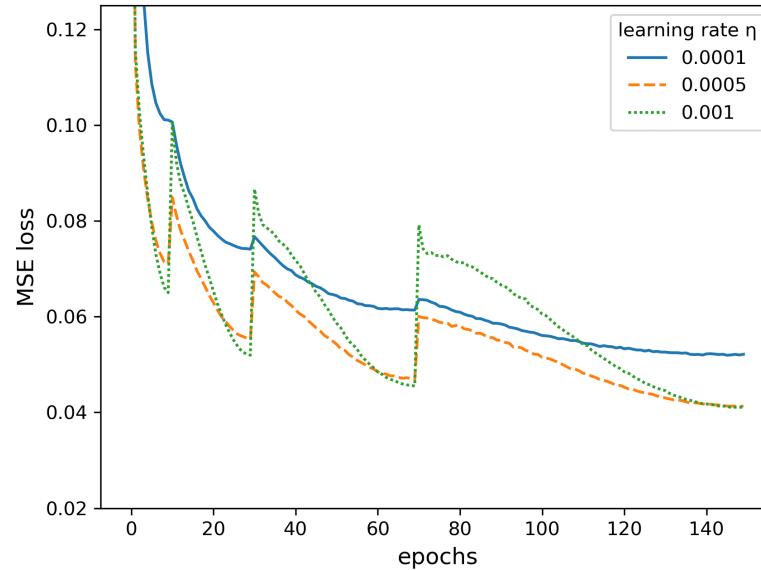


Visualisation: Stepping

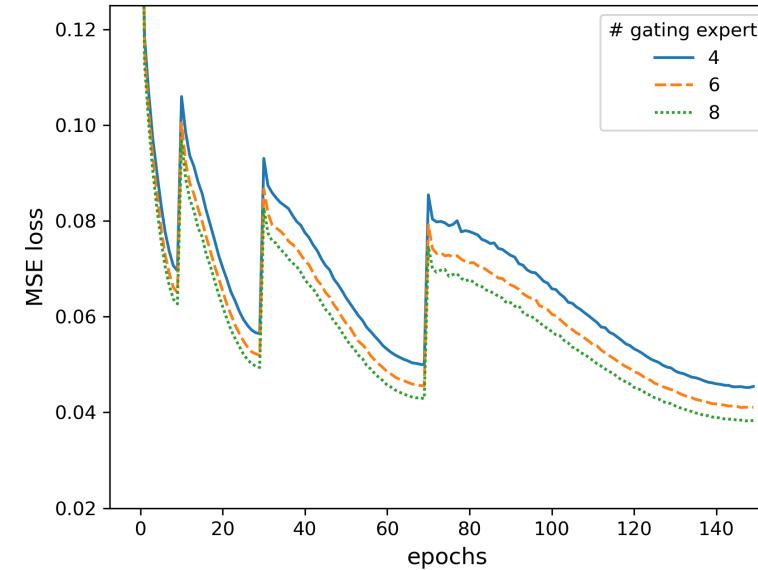


Hyperparameter Tuning

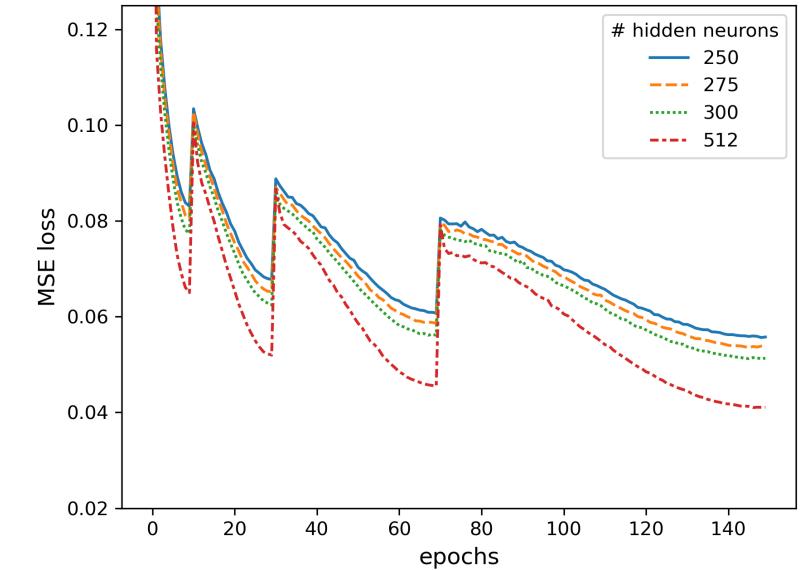
Loss plot for tuning learning rate



Loss plot for tuning number of gating experts



Loss plot for tuning number of hidden neurons



☐ Best parameters:

- Learning rate = 0.001
- Num expert weights = 8
- Num MPN hidden neurons = 512

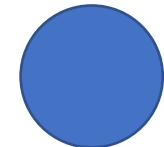
Punch control

Evaluation Metrics

- ❑ Punch Accuracy: How many punches are good enough?

$$\text{accuracy} = \begin{cases} 1; & \mathbf{l^2}(x, y) < p_{threshold} \\ 0; & \mathbf{l^2}(x, y) \geq p_{threshold} \end{cases}$$

$$\text{PA} = \frac{B}{Z} \times 100$$



Average German male head

- ❑ Punch Error: How close do we get to target?

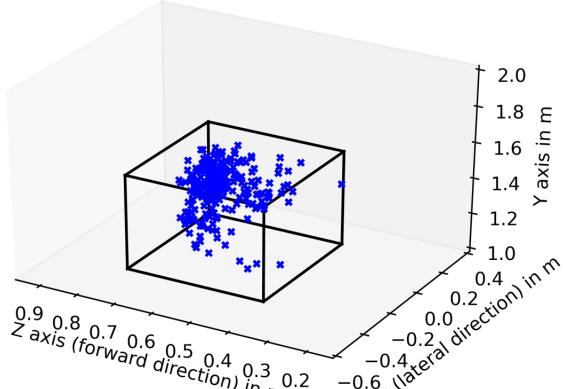
$$\text{PE}(\mathbf{W}, \mathbf{P}) = \frac{1}{B} \sum_{n=1}^B \mathbf{l^2}(\mathbf{w}_n, \mathbf{p}_n)$$

- ❑ Foot Skating Error: Does the character float?

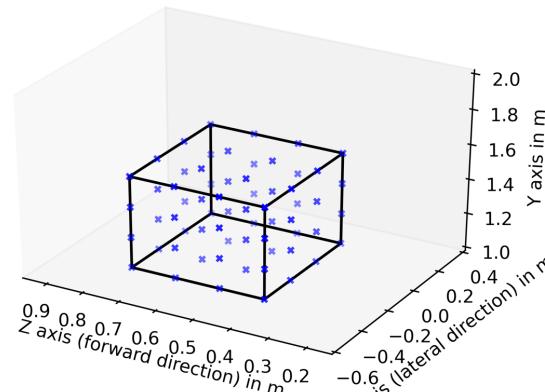
$$\text{FSE} = \frac{1}{2} \sum_{l=1}^2 d_l \left(2 - 2^{\left(\frac{h_l}{H} \right)} \right)$$

Punch control Setup

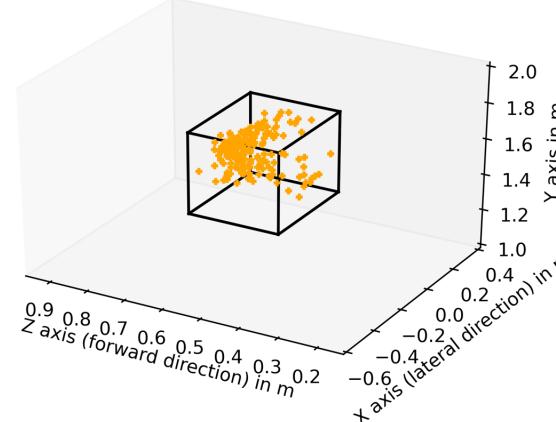
Dataset left punch targets



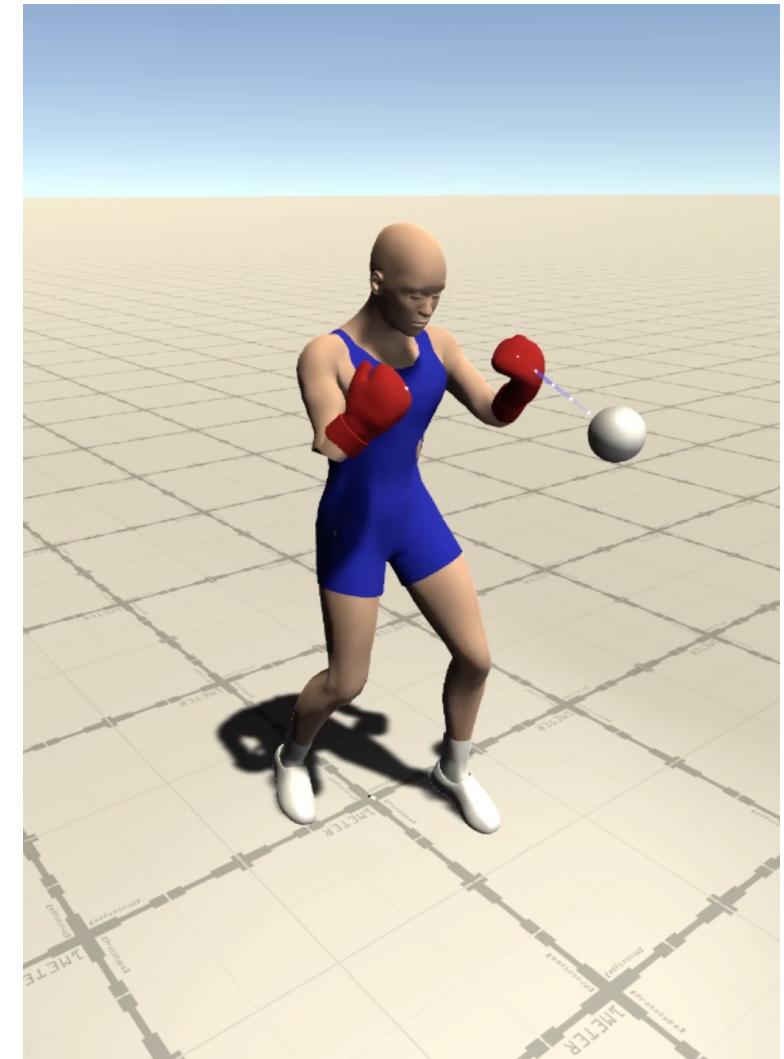
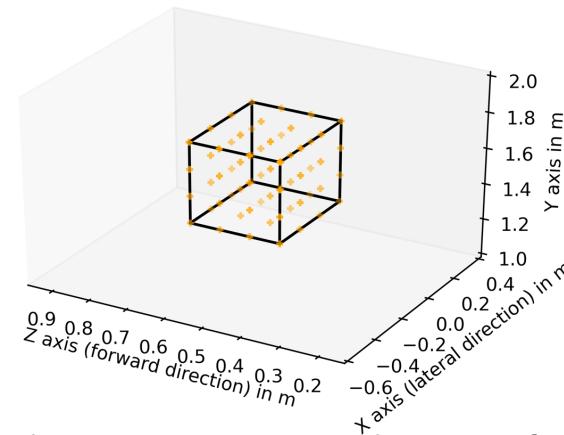
Uniform left punch targets



Dataset right punch targets



Uniform right punch targets



Simulating Fast-Movements with Mixture-of-Expert models

Punch control

Trajectory Sampling

❑ Assumption:

- Traj similar to dataset punch
→ more accurate punches
- Models with trajectory window
 - covering approx. 27 frames (0.45s)

❑ Observation:

- w=14, fs=3 leads to best accuracy.
- Best model has somewhat high FSE.
- Accuracy of left hand always higher than right hand.

❑ Conclusion:

Sample according to dataset punches

w (frames)	fs (frames)	$PE_{overall}$ (cm)	$PA_{overall}$ (%)	FSE (cm)
4	1	11.43	20.31	0.285
6	1	11.29	28.91	0.305
8	1	11.02	28.91	0.332
10	1	11.32	32.81	0.336
12	1	11.12	34.38	0.403
14	1	11.08	37.50	0.341
16	1	11.04	26.56	0.418
18	1	10.92	30.47	0.378
20	1	11.30	28.91	0.404
12	2	10.95	37.50	0.321
14	2	10.20	36.72	0.320
16	2	10.22	39.06	0.335
18	2	10.85	42.97	0.350
20	2	11.07	33.59	0.804
10	3	11.00	45.31	0.549
14	3	11.38	53.91	0.667
16	3	11.25	40.62	0.777
18	3	11.12	42.97	0.846

Punch control Ablation Study

❑ Assumption:

- Sufficient trajectory information needed
- 3 models using w=14 and fs=3

❑ Observation:

- Fewer trajectory variables leads to more steps
- All trajectory variables correctly move the hand to punch

❑ Conclusion:

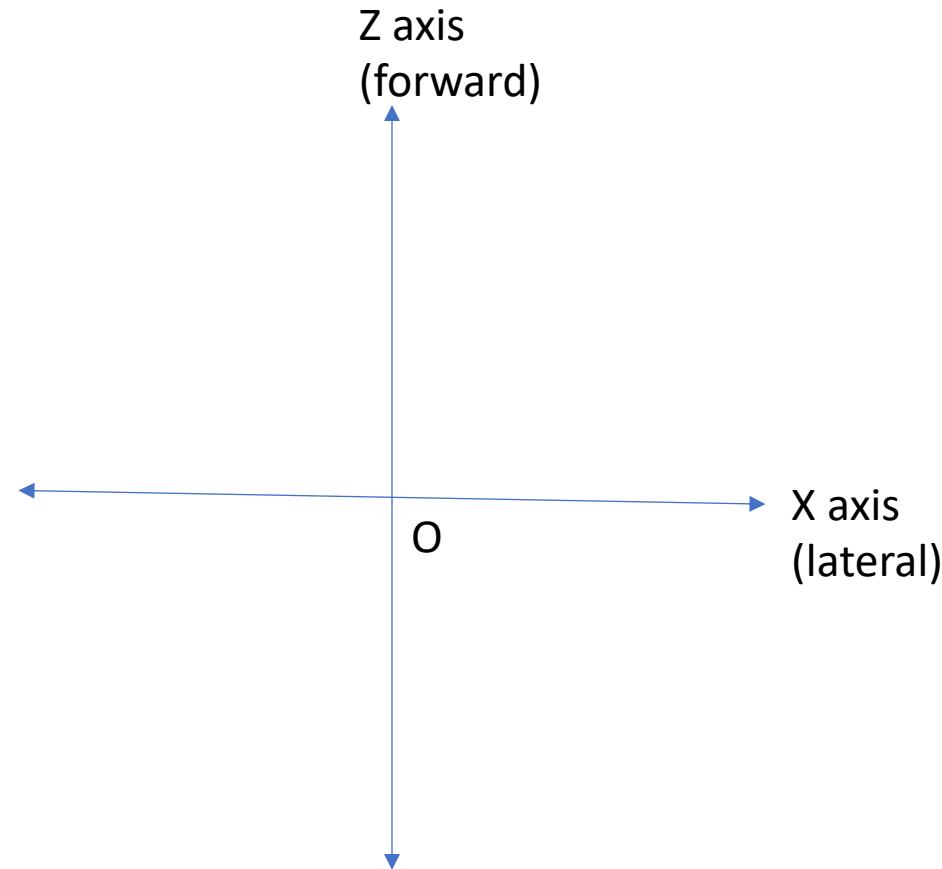
Traj pos + vel → accurate punches

Wrist trajectory variables	$PE_{overall}$ (cm)	$PA_{overall}$ (%)	FSE (cm)
none	11.18	31.25	1.177
pos	12.13	35.94	0.980
pos + vel	11.38	53.91	0.667

Stepping control

Setup

- Two scenarios:
 - Step forward
 - Step backward
- Stepping executed along Z axis
- Duration: 300 frames (5s)



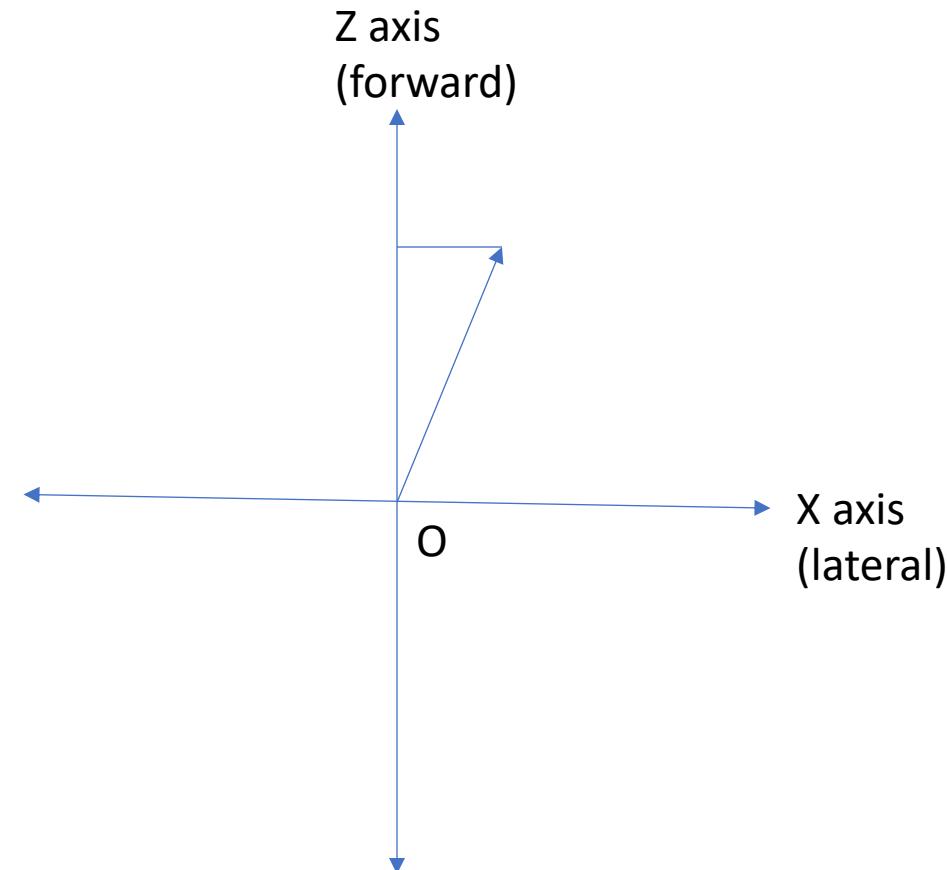
Stepping control Evaluation Metrics

- ☐ Stepping Path Error (SPE): Path following capability

$$\text{SPE}(\mathbf{G}, \mathbf{E}) = \frac{1}{N} \sum_{f=1}^N \mathbf{l}^2(\mathbf{g}_f, \mathbf{e}_f)$$

- ☐ Foot Skating Error (FSE): Does the character float?

$$\text{FSE} = \frac{1}{2} \sum_{l=1}^2 d_l \left(2 - 2^{\left(\frac{h_l}{H} \right)} \right)$$



Stepping control

Trajectory Sampling

❑ Assumption:

- Trajectory window similar to average stepping duration
→ better stepping
- Trained models: 0.3s to 2s windows
- Dataset average: 20 frames (0.3s)

w (frames)	fs (frames)	$SPE_{overall}$ (cm)	FSE (cm)
10	2	33.61	0.52
12	2	37.36	0.70
14	2	49.75	0.76
16	2	68.92	0.56
18	2	65.23	0.97
10	3	37.84	1.28
8	4	63.42	1.36
14	4	52.14	2.59

❑ Observation:

- Forward stepping better than backward stepping

❑ Conclusion:

Sample according to dataset stepping action

General Discussion

- ❑ Amount of data: 10 mins v/s 20 hrs
- ❑ Hyperparameter tuning led to sharper motions
- ❑ At least traj pos and vel → accurate punches
- ❑ Trajectory should be in line with dataset
- ❑ Controller fixes:
 - Punch target management
 - Punch termination

Limitations

- ❑ Less data
- ❑ Better instructions during data acquisition
- ❑ Automatic annotation
- ❑ Synthesising rotations



Future Work

- ❑ Amount of data for neural synthesis
- ❑ Update motion states
 - around boxing ring
 - around opponent
 - include rotations
- ❑ Other targeted actions
- ❑ Dynamic models

Conclusions

- ❑ Synthesised non-periodic, fast boxing actions
- ❑ Tune MoE models
- ❑ Trajectory variables necessary
- ❑ Trajectory sampling as per dataset
- ❑ Controller essential

References

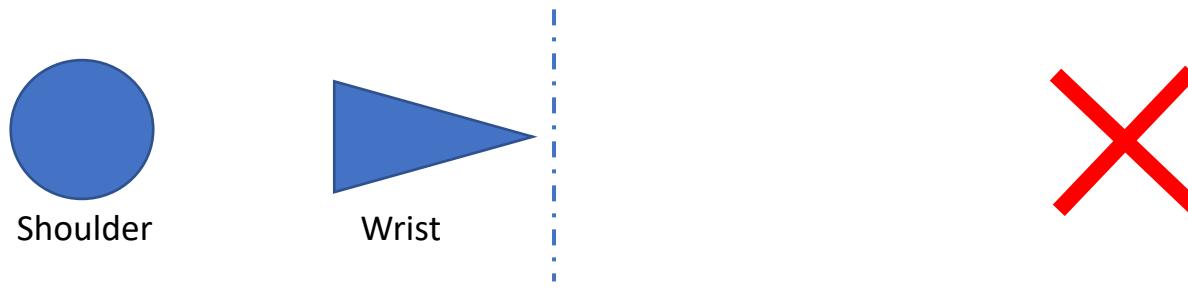
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- Sebastian Starke, Yiwei Zhao, Taku Komura, and Kazi Zaman. 2020. Local motion phases for learning multi-contact character movements. *ACM Trans. Graph.* 39, 4, Article 54 (July 2020), 14 pages.
- Sebastian Starke, Yiwei Zhao, Fabio Zinno, and Taku Komura. 2021. Neural animation layering for synthesizing martial arts movements. *ACM Trans. Graph.* 40, 4, Article 92 (August 2021), 16 pages.

Thank You

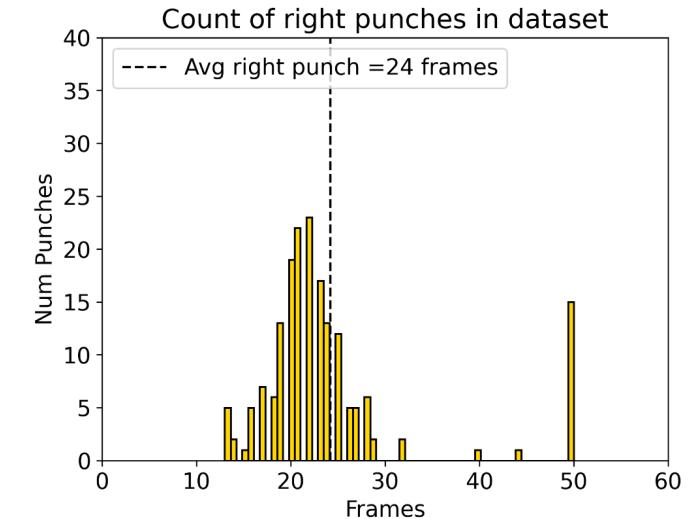
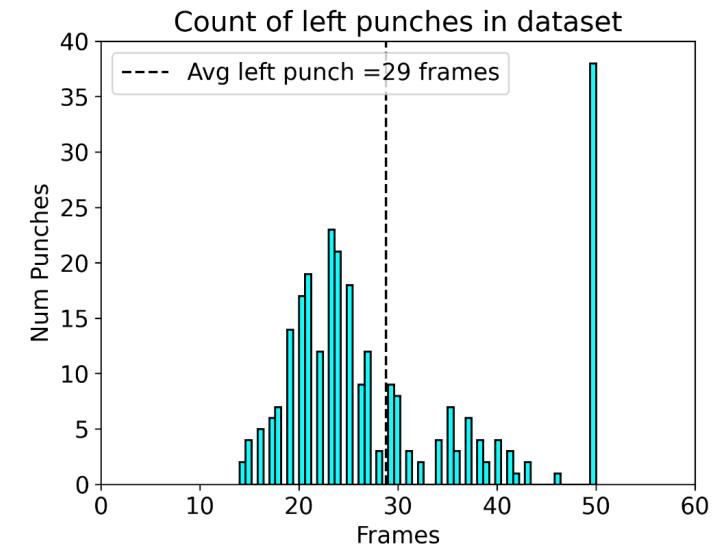
Supplimentary slides

Data Acquisition: Punch annotation limitation

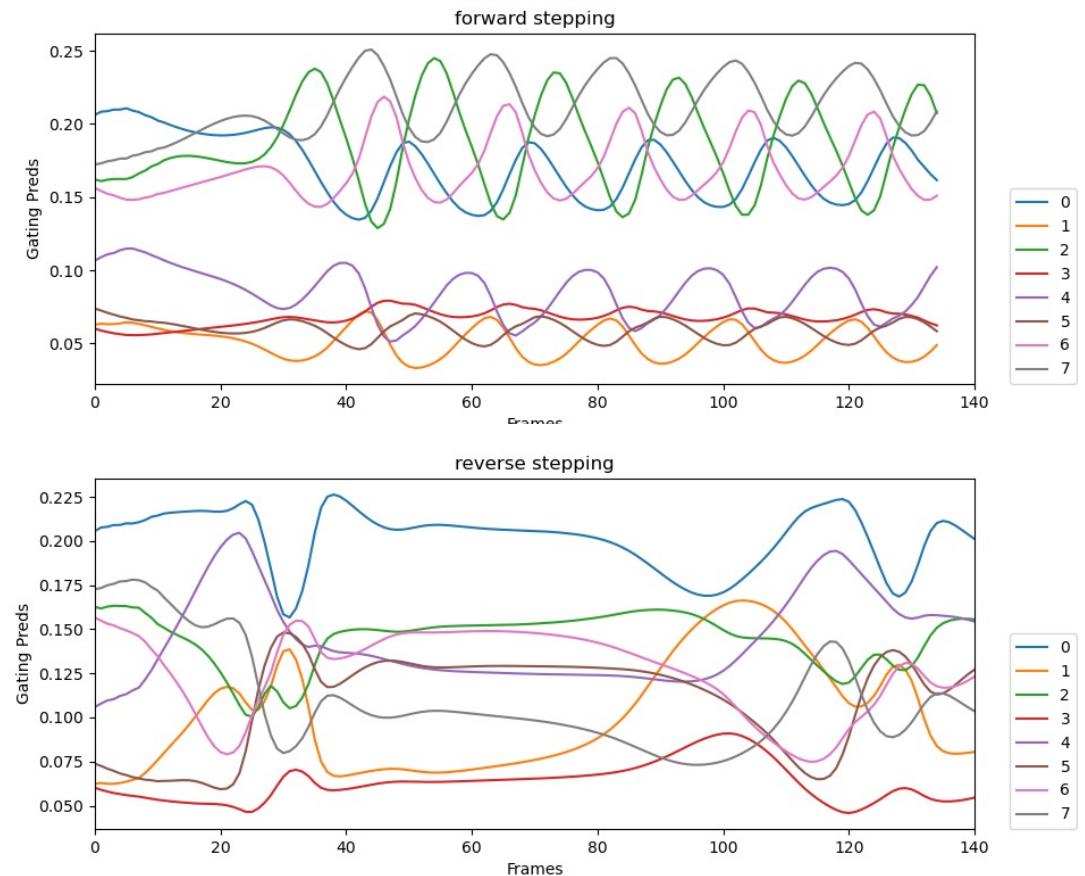
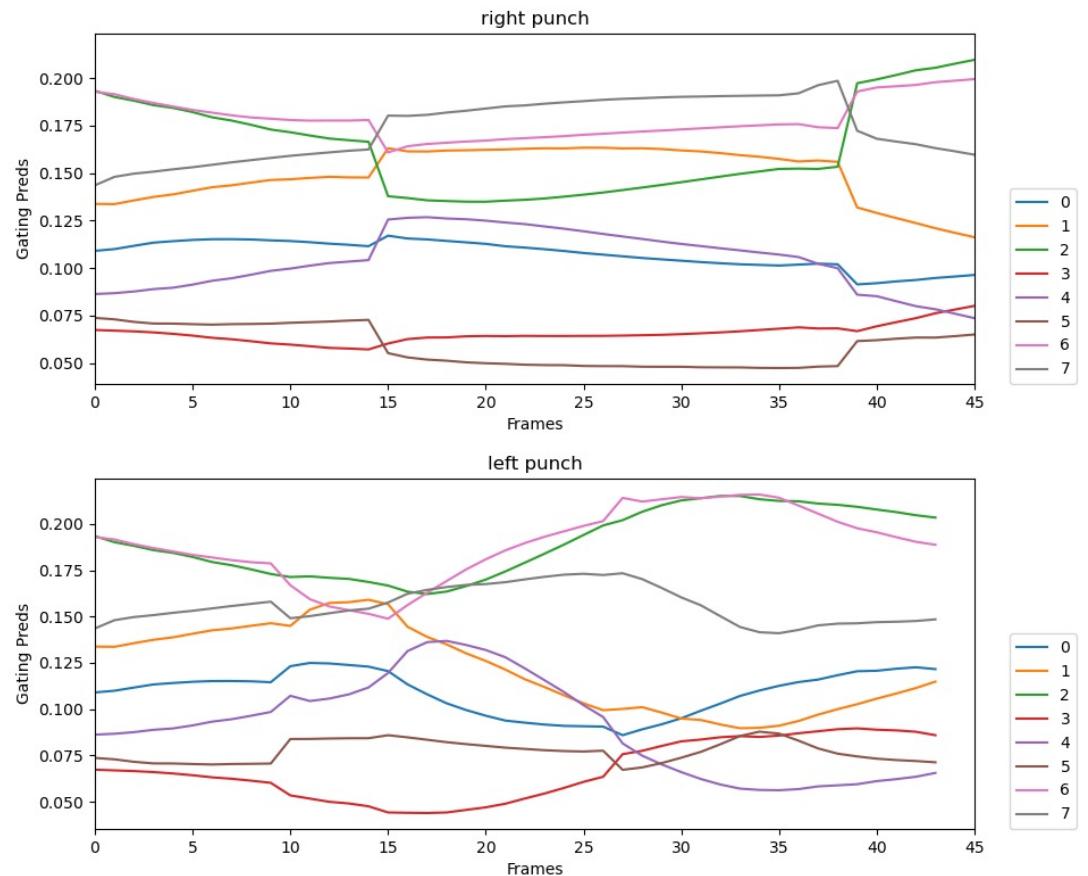
- Finding search threshold hard



- Drop or keep slow punches?



Boxing neural model: Gating network output plots



Boxing controller system: Root Transformation

- Local positions $lp_i = r_f * (gp_i - gp_0|_{y=0})$
- Local velocities and directions $l_i = r_f * g_i$
- Rotations:
 - Compute forward facing directions
 - Vector between shoulder joints
 - Upward direction vector
 - Cross product gives forward directions
 - Rotations between user specified dir and fwd dir

Boxing controller system: Merge User input

- Trajectory root position

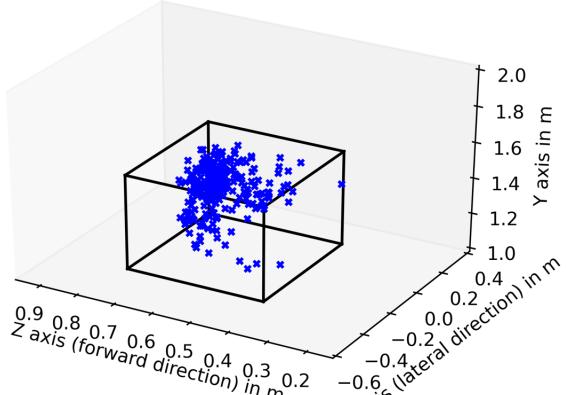
$$trp_i = trp_{i-1} + \left(1 - \left(\frac{(i - \frac{w}{2})}{\frac{w}{2}}\right)^\tau\right) \times (trp_i - trp_{i-1}) + \left(\frac{(i - \frac{w}{2})}{\frac{w}{2}}\right)^\tau \times v_{target}$$

- Trajectory wrist position

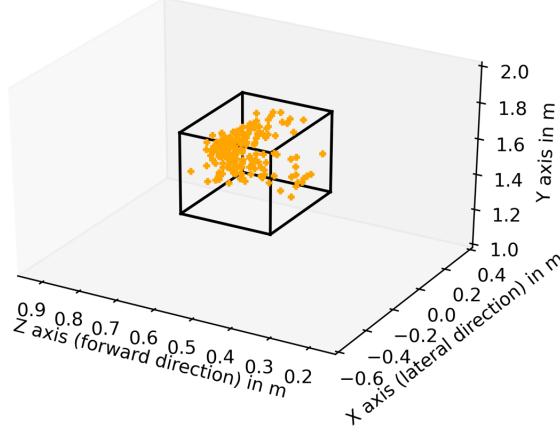
$$thp_i = thp_{i-1} + ((pt - hp_i) \times st) \times i$$

Punch control: Punch targets

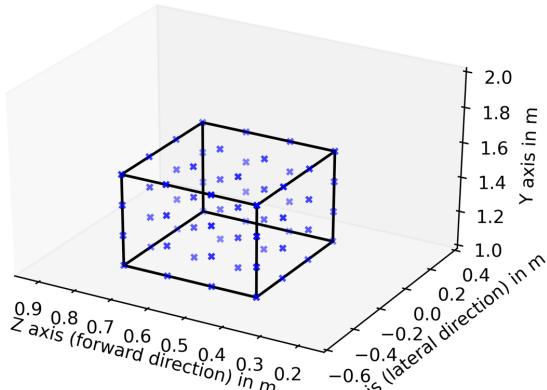
Dataset left punch targets



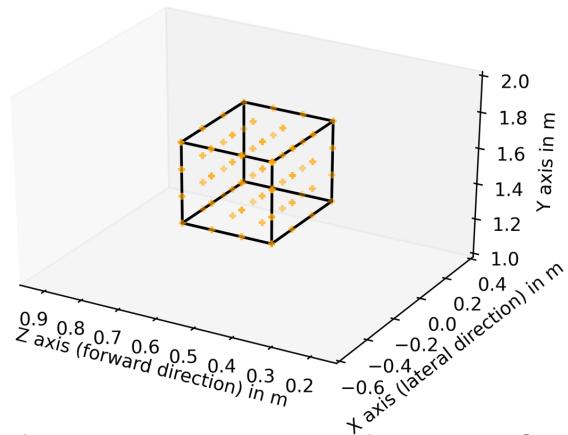
Dataset right punch targets



Uniform left punch targets

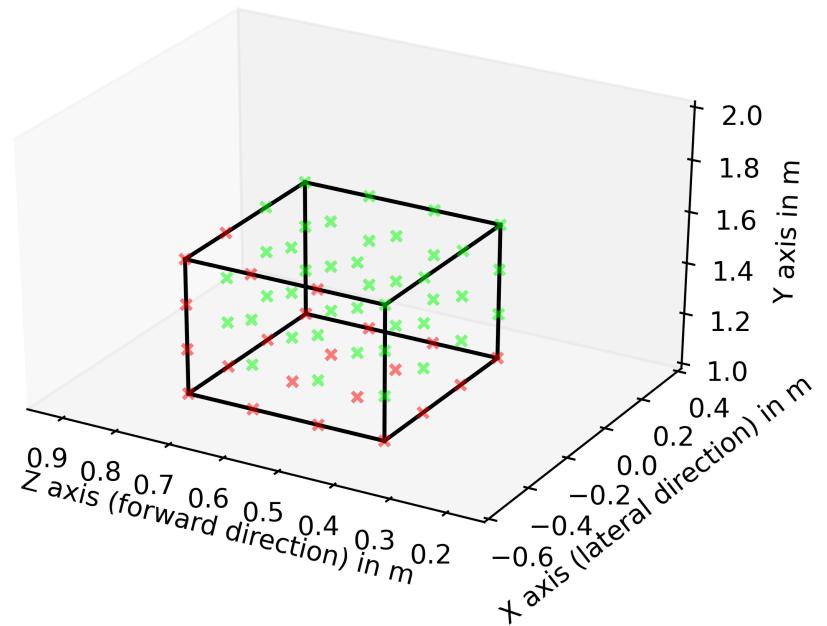


Uniform right punch targets

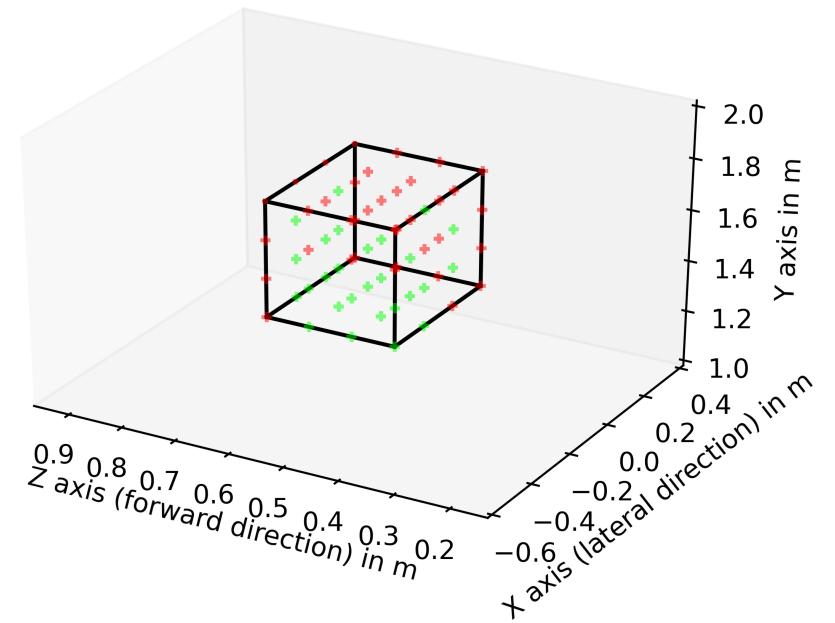


Punch control: Punch accuracy plot (Traj Sampling)

Uniform left punch targets
with accuracy



Uniform right punch targets
with accuracy



Punch control

Evaluation Metrics

- ❑ Punch Accuracy: How many punches are good enough?

$$\text{accuracy} = \begin{cases} 1; & \mathbf{l^2}(x, y) < p_{threshold} \\ 0; & \mathbf{l^2}(x, y) \geq p_{threshold} \end{cases}$$

$$\text{PA} = \frac{B}{Z} \times 100$$



Average German male head

- ❑ Punch Error: How close do we get to target?

$$\text{PE}(\mathbf{W}, \mathbf{P}) = \frac{1}{B} \sum_{n=1}^B \text{MSE}(\mathbf{w}_n, \mathbf{p}_n)$$

- ❑ Foot Skating Error: Does the character float?

$$\text{FSE} = \frac{1}{2} \sum_{l=1}^2 d_l \left(2 - 2^{\left(\frac{h_l}{H} \right)} \right)$$

Punch control

Trajectory Sampling

❑ Assumption:

- Traj similar to dataset punch
→ more accurate punches
- Models with trajectory window
 - covering approx. 27 frames (0.45s)

❑ Observation:

- w=14, fs=3 leads to best accuracy.
- Best model has somewhat high FSE.
- Accuracy of left hand always higher than right hand.

❑ Conclusion:

Sample according to dataset punches

w (frames)	fs (frames)	$PE_{overall}$ (cm)	$PA_{overall}$ (%)	FSE (cm)
4	1	11.43	20.31	0.285
6	1	11.29	28.91	0.305
8	1	11.02	28.91	0.332
10	1	11.32	32.81	0.336
12	1	11.12	34.38	0.403
14	1	11.08	37.50	0.341
16	1	11.04	26.56	0.418
18	1	10.92	30.47	0.378
20	1	11.30	28.91	0.404
12	2	10.95	37.50	0.321
14	2	10.20	36.72	0.320
16	2	10.22	39.06	0.335
18	2	10.85	42.97	0.350
20	2	11.07	33.59	0.804
10	3	11.00	45.31	0.549
14	3	11.38	53.91	0.667
16	3	11.25	40.62	0.777
18	3	11.12	42.97	0.846

w (frames)	fs (frames)	$PE_{overall}$ (cm ²)	$PA_{overall}$ (%)	FSE (cm)
4	1	44.83	20.31	0.285
6	1	43.65	28.91	0.305
8	1	41.24	28.91	0.332
10	1	43.79	32.81	0.336
12	1	42.19	34.38	0.403
14	1	42.06	37.50	0.341
16	1	41.51	26.56	0.418
18	1	40.57	30.47	0.378
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Punch control Ablation Study

❑ Assumption:

- Sufficient trajectory information needed
→ accurate punches
- 3 models using w=14 and fs=3

Wrist trajectory variables	$PE_{overall}$ (cm)	$PA_{overall}$ (%)	FSE (cm)
none	11.18	31.25	1.177
pos	12.13	35.94	0.980
pos + vel	11.38	53.91	0.667

Wrist trajectory variables	$PE_{overall}$ (cm^2)	$PA_{overall}$ (%)	FSE (cm)
none	44.77	31.25	1.177
pos	50.02	35.94	0.980
pos + vel	44.19	53.91	0.667

❑ Observation:

- Fewer trajectory variables leads to more steps
- All trajectory variables correctly move the hand to punch

❑ Conclusion:

Traj pos + vel → accurate punches

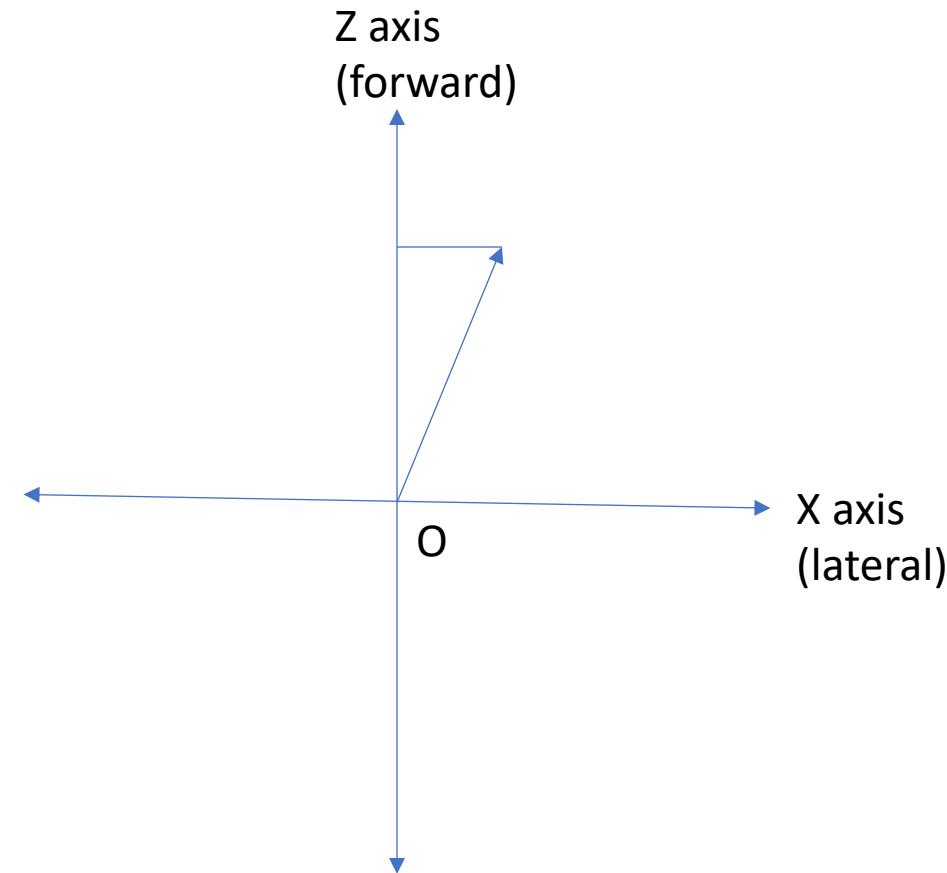
Stepping control Evaluation Metrics

- ☐ Stepping Path Error (SPE): Path following capability

$$\text{SPE}(\mathbf{G}, \mathbf{E}) = \frac{1}{N} \sum_{f=1}^N \text{MSE}(\mathbf{g}_f, \mathbf{e}_f)$$

- ☐ Foot Skating Error (FSE): Does the character float?

$$\text{FSE} = \frac{1}{2} \sum_{l=1}^2 d_l \left(2 - 2^{\left(\frac{h_l}{H} \right)} \right)$$



Stepping control

Trajectory Sampling

❑ Assumption:

- Trajectory similar to average stepping duration
→ better stepping
- Trained models: 0.3s to 2s windows
- Dataset average: 20 frames (0.3s)

❑ Observation:

- Forward stepping better than backward stepping

❑ Conclusion:

Sample according to dataset stepping action

w (frames)	fs (frames)	$SPE_{overall}$ (cm)	FSE (cm)
10	2	33.61	0.52
12	2	37.36	0.70
14	2	49.75	0.76
16	2	68.92	0.56
18	2	65.23	0.97
10	3	37.84	1.28
8	4	63.42	1.36
14	4	52.14	2.59

w (frames)	fs (frames)	$SPE_{overall}$ (cm ²)	FSE (cm)
10	2	746.29	0.52
12	2	1059.91	0.70
14	2	2773.14	0.76
16	2	3589.26	0.56
18	2	2959.33	0.97
10	3	1234.06	1.28
8	4	4724.17	1.36
14	4	3129.29	2.59

Punch control

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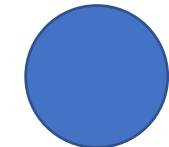
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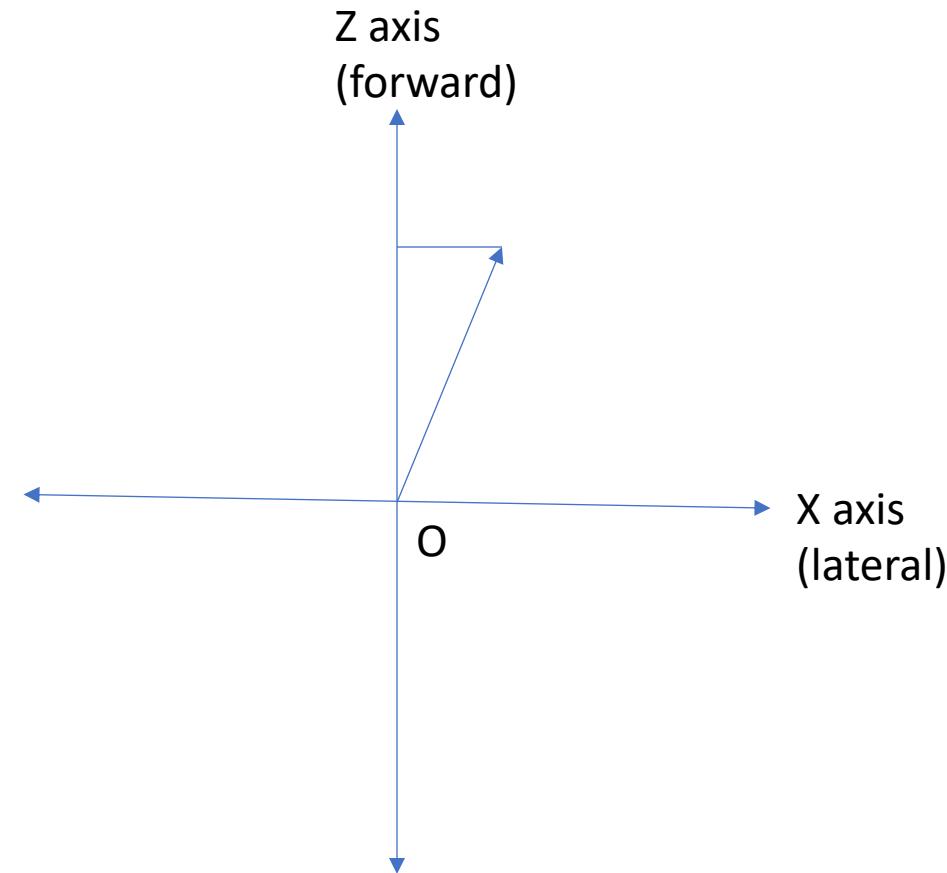
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