Friedrich-Alexander-Universität
Technische Fakultät

SSPINNpose: Self-supervised learning of biomechanical variables without ground truth

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Machine Learning and PDEs Workshop
Research Center for Mathematics of Data
30.04.2025

Understanding Human Movement

Motivation

Diagnosis and Disease Monitoring

Performance Optimization

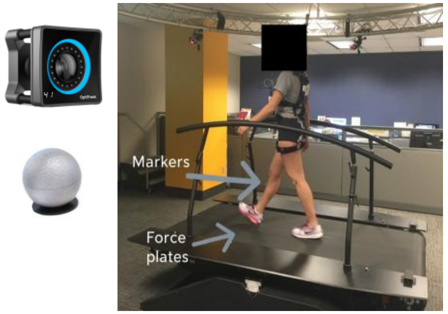
Rehabilitation

Device Optimization

Movement Analysis

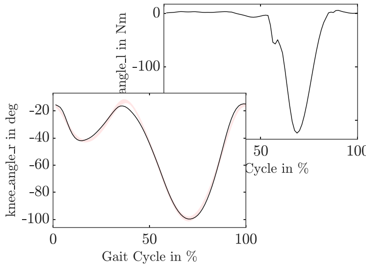
Standard Approach: Optical Motion Capture

Motion Laboratory

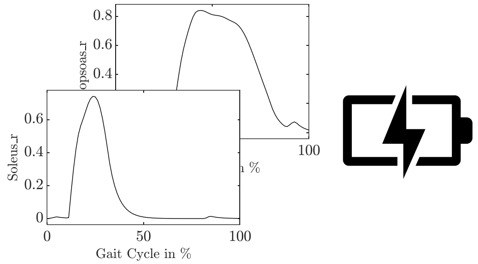


Musculoskeletal Model

Joint Angles and Moments



Muscle States and Energy Expenditure



$$M(\boldsymbol{q})\ddot{\boldsymbol{q}} + C(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + G(\boldsymbol{q}) = \boldsymbol{\tau} + J(\boldsymbol{q})^T \boldsymbol{F}_{ext}$$

$$\boldsymbol{F}_{CE} = \mathbf{a} f(\mathbf{l}_{CE}) g(\mathbf{v}_{\mathrm{CE}})\mathbf{F}_{iso}$$

$$\dot{\boldsymbol{a}} = \left(\frac{\mathbf{u}}{T_{act}} + \frac{1-\mathbf{u}}{T_{deact}}\right)(\mathbf{u}-\mathbf{a})$$

$$\min_{q_i} \sum_j \left|\left|\boldsymbol{r}_j - \boldsymbol{f}_j(q_i)\right|\right|^2$$

$$\min_{\tau_i}\sum_i \left|\left|\boldsymbol{\tau} + J(\boldsymbol{q})^T\boldsymbol{F}_{ext} - M(\boldsymbol{q})\ddot{\boldsymbol{q}} + C(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + G(\boldsymbol{q})\right|\right|^2$$

$$\min_{a_n}\sum_n a^3$$

Movement Analysis

Standard Approach: Optical Motion Capture

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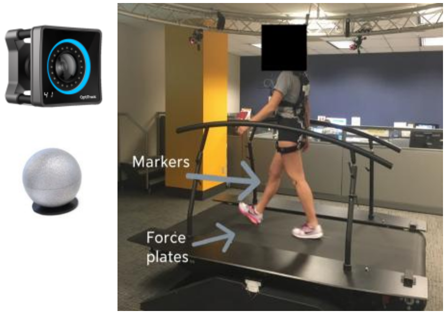

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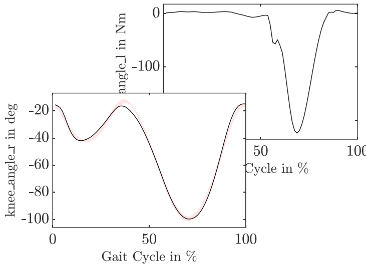

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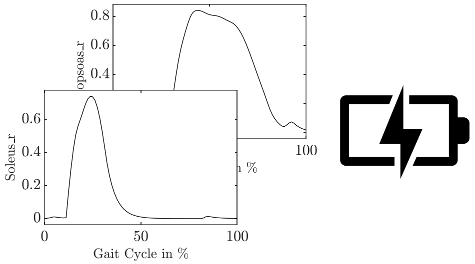
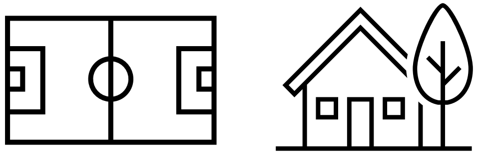
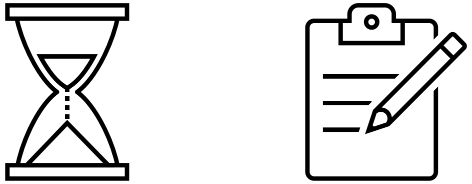


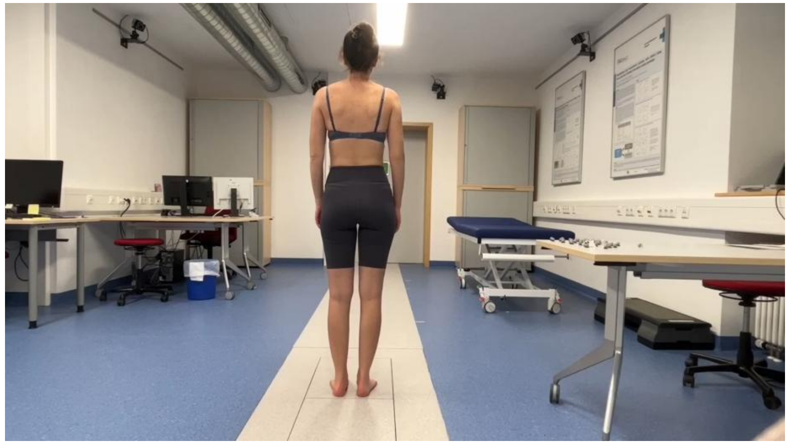
Challenges

- Restricted environment



- Time consuming

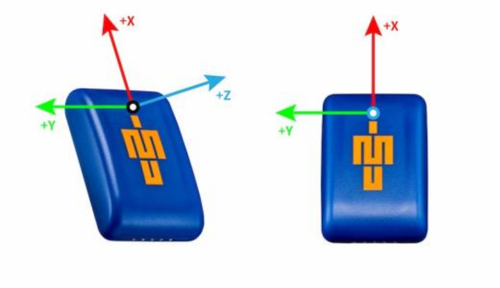




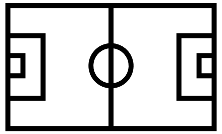
Inertial Sensors

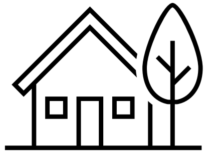
Measurements Anywhere

Measure
- Accelerations
- Angular velocities



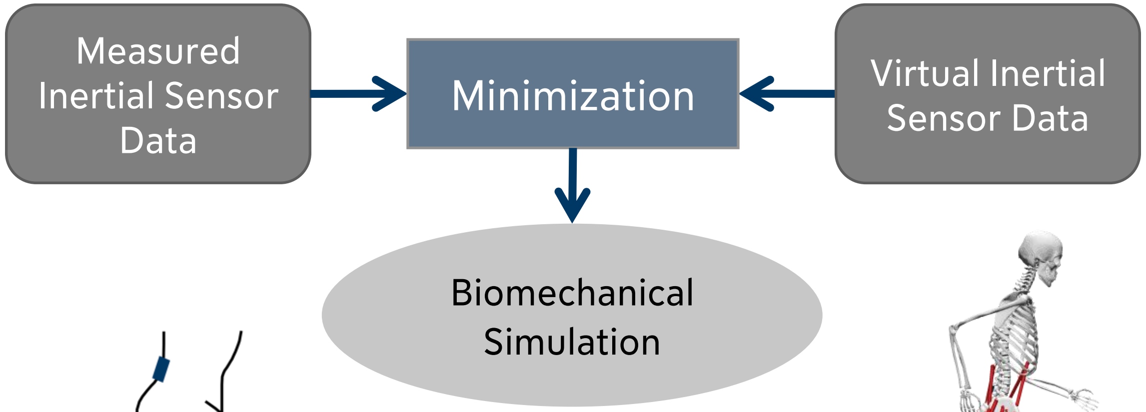
Advantages
- Useable anywhere
- Affordable

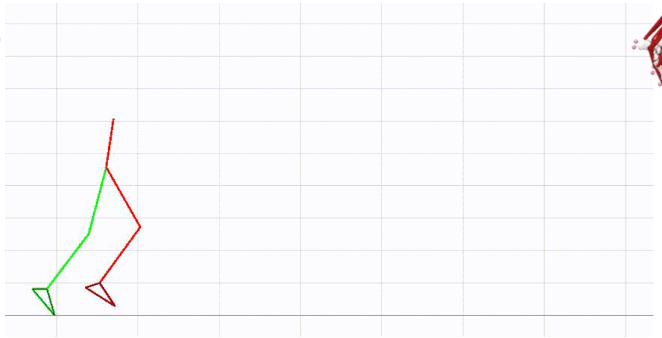


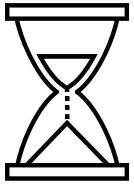


Disadvantages
- No global positions
- Integration drift

Optimal control-based estimation







Dorschky et al., *J Biomech*, 2019; Nitschke et al., *Front Bioeng Biotech*, 2024; Dorschky, Nitschke, et al., *Front Bioeng Biotech*, 2025

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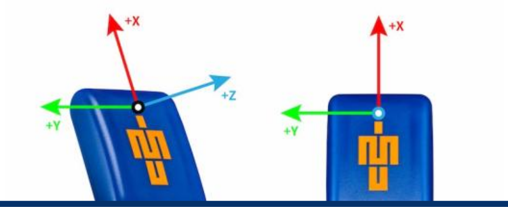


Optimal control-based estimation

Measured Inertial Sensor → Minimization ← Virtual Inertial Sensor Data

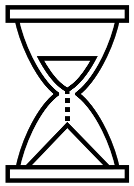
Advantages

- Useable anyw
- Affordable

Can we use machine learning to map inertial sensor data to biomechanical variables?

Disadvantages

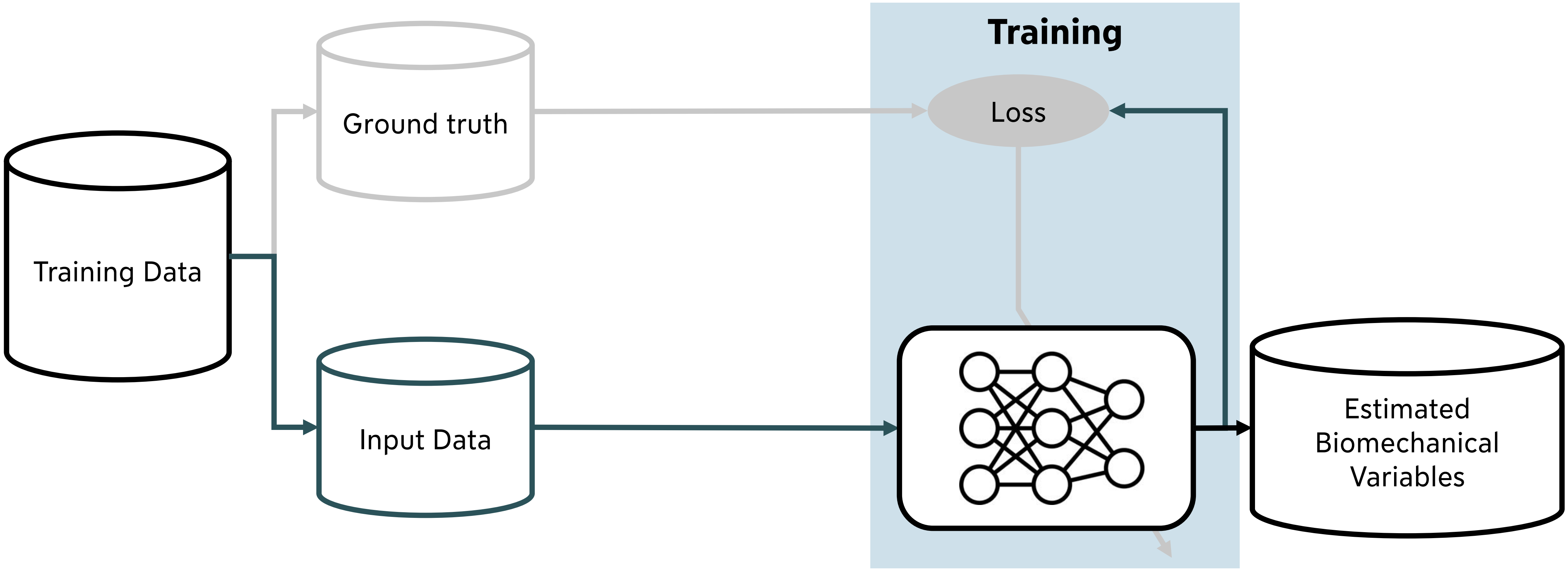
- No global positions
- Integration drift



Dorschky et al., *J Biomech*, 2019; Nitschke et al., *Front Bioeng Biotech*, 2024; Dorschky, Nitschke, et al., *Front Bioeng Biotech*, 2025

Supervised Learning

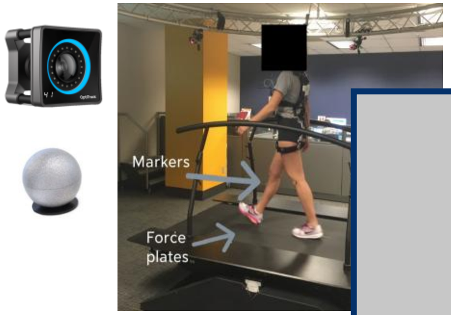
Application in Biomechanics



Supervised Learning

Application in Biomechanics

Motion Laboratory



Musculoskeletal Model

Joint Angles and Moments

Muscle States and Energy Expenditure

We cannot directly measure the ground truth

Training Data

Input Data

Estimated Biomechanical Variables

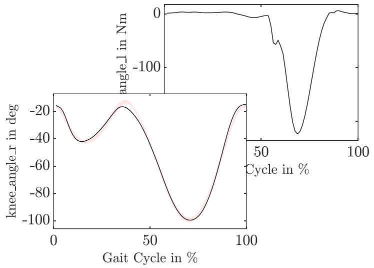
Creating a Ground Truth

Combining Inertial and Optical Motion Capture

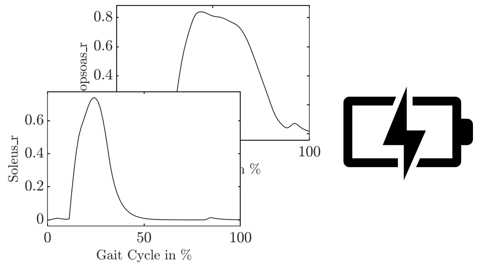
Motion Laboratory

Musculoskeletal Model

Joint Angles and Moments



Muscle States and Energy Expenditure



Ground truth variables through optical motion capture

One experiment with two measurements

- Optical motion capture
- Inertial sensor measurements

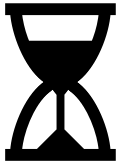
→Synchronization important

Data Availability

Requirements and Challenges

Variation is required of usability and applicability

- Movements
- Participants
- Sensor positions



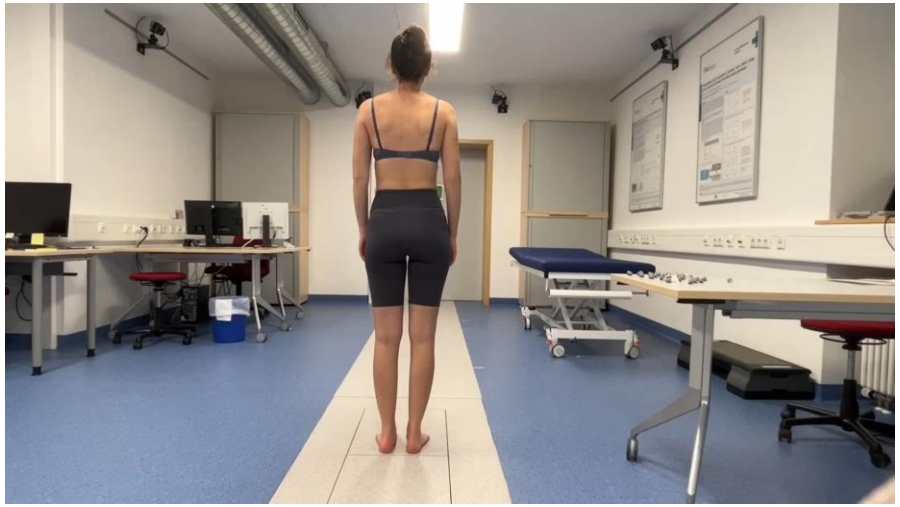
Optical motion capture

- Limited capture volume
- Long preparation (1 hr of marker placement)

→Large datasets are rare

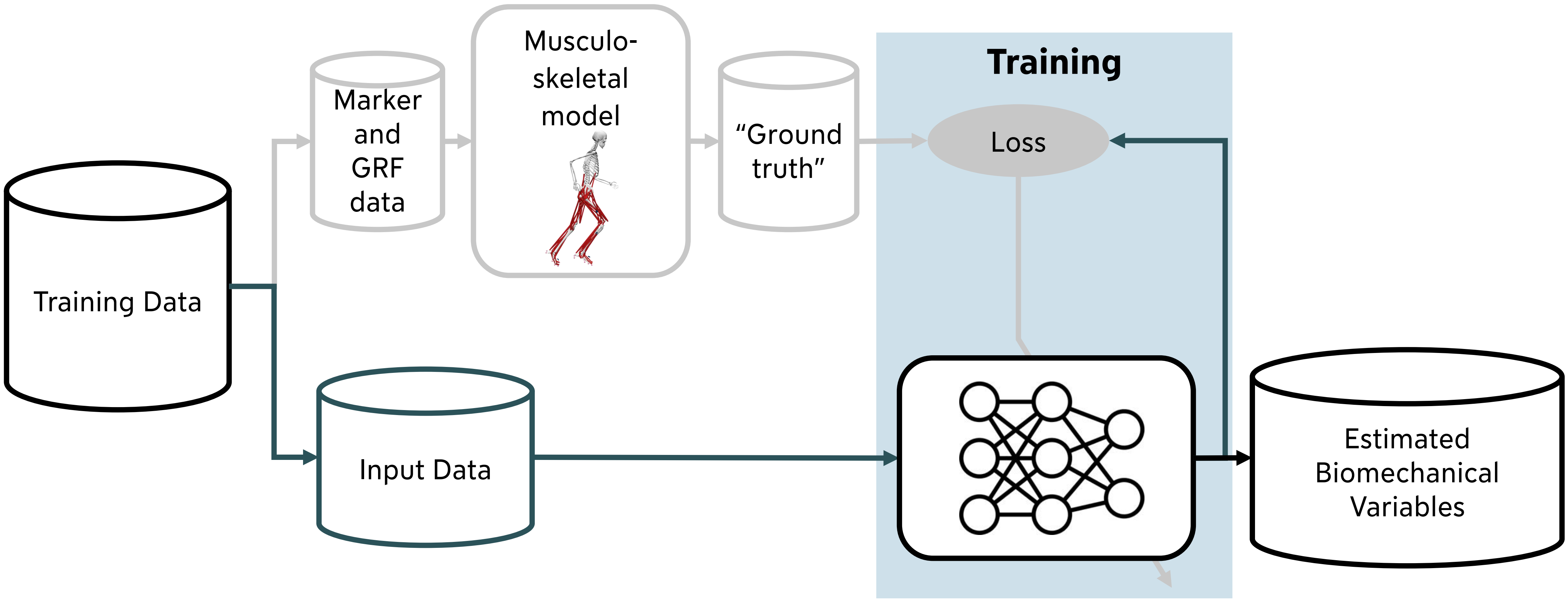
- Some university or hospital labs have 20+ years of data available (e.g., Johnson et al., *IEEE TBME*, 2020)

→Combining datasets is tricky (Fleischmann et al., *ACM TIST*, 2024)



Supervised Learning in Biomechanics

Ground truth is not measured directly



Musculoskeletal Dynamics

Differential Equations

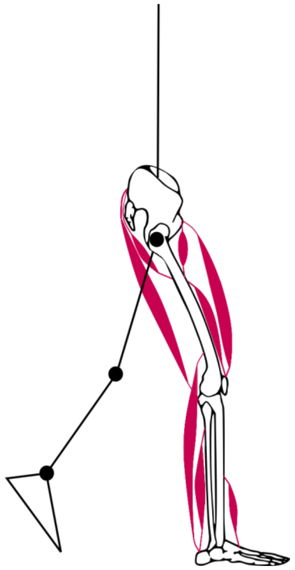
Multibody dynamics of skeleton

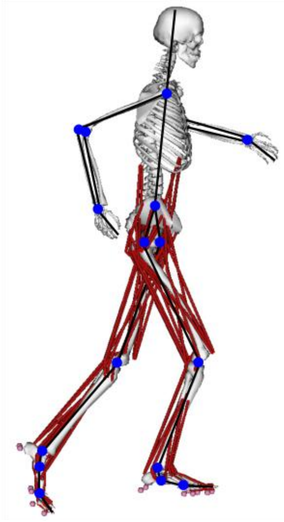
$$M(\boldsymbol{q})\ddot{\boldsymbol{q}} + C(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + G(\boldsymbol{q}) = d\boldsymbol{F}_{SEE} + J(\boldsymbol{q})^T\boldsymbol{F}_{ext}$$

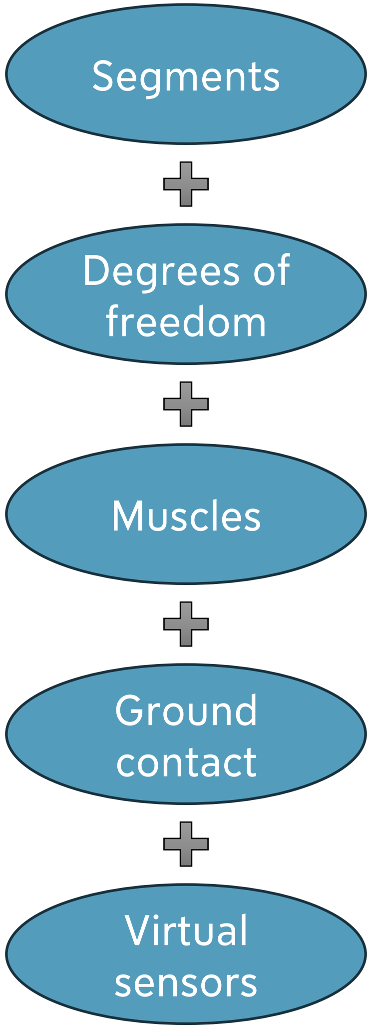
Muscle dynamics

$$\dot{\mathbf{a}}(t) = \left(\frac{\mathbf{u}(t)}{T_{act}} + \frac{1-\mathbf{u}(t)}{T_{deact}}\right)\left(\mathbf{u}(t) - \mathbf{a}(t)\right)$$

$$\mathbf{a}(t) f\left(\mathbf{l}_{CE}(t)\right) g\left(\mathbf{v}_{CE}(t)\right)\mathbf{F}_{iso} + \mathbf{F}_{PEE}(t) = \mathbf{F}_{SEE}(t)$$







Model parameters

- From cadaver studies
- Example: Dempster (1955)
  - 10 elderly white males

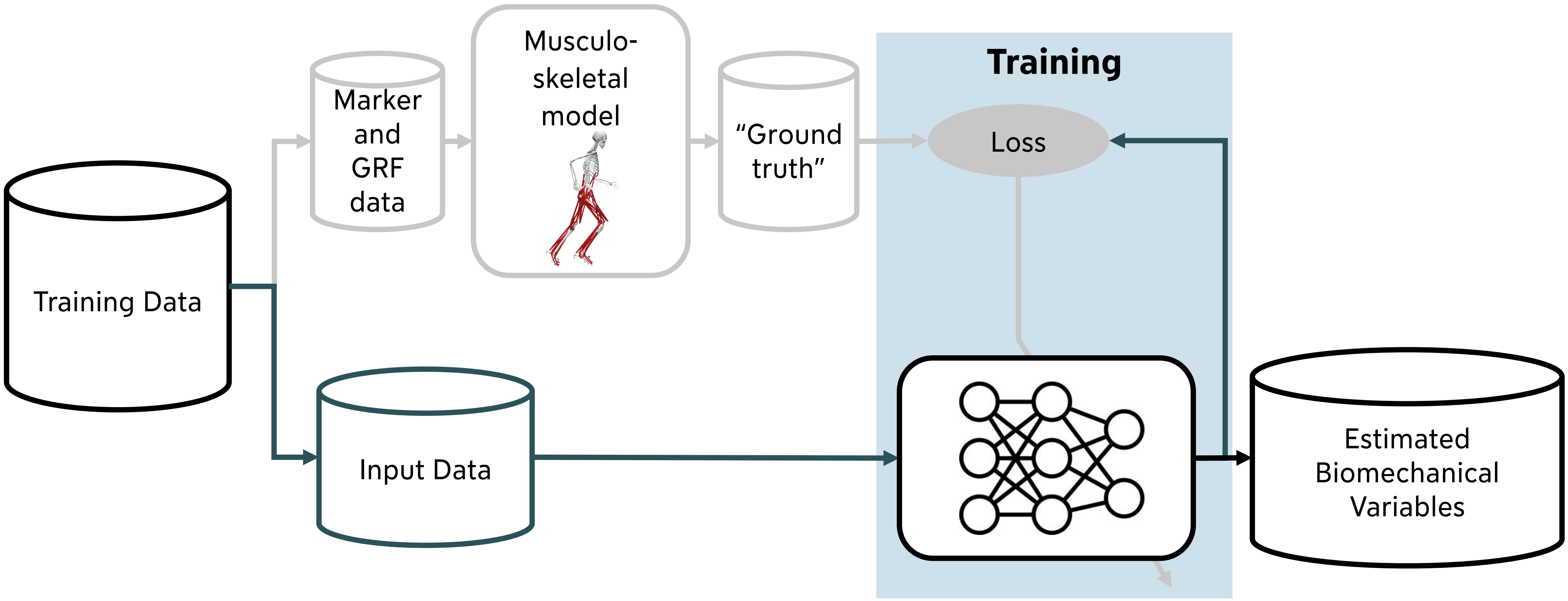
TABLE 4.1 Anthropometric Data

Segment	Definition	Segment Weight/Total Body Weight	Center of Mass/Segment Length: Proximal	Center of Mass/Segment Length: Distal	Radius of Gyration/Segment Length: C of G	Radius of Gyration/Segment Length: Proximal	Radius of Gyration/Segment Length: Distal	Density
Hand	Wrist axis/knuckle II middle finger	0.006 M	0.506	0.494 P	0.297	0.587	0.577 M	1.16
Forearm	Elbow axis/ulnar styloid	0.016 M	0.430	0.570 P	0.303	0.526	0.647 M	1.13
Upper arm	Glenohumeral axis/elbow axis	0.028 M	0.436	0.564 P	0.322	0.542	0.645 M	1.07
Forearm and hand	Elbow axis/ulnar styloid	0.022 M	0.682	0.318 P	0.468	0.827	0.565 P	1.14
Total arm	Glenohumeral joint/ulnar styloid	0.050 M	0.530	0.470 P	0.368	0.645	0.596 P	1.11
Foot	Lateral malleolus/head metatarsal II	0.0145 M	0.50	0.50 P	0.475	0.690	0.690 P	1.10
Leg	Femoral condyles/medial malleolus	0.0465 M	0.433	0.567 P	0.302	0.528	0.643 M	1.09
Thigh	Greater trochanter/femoral condyles	0.100 M	0.433	0.567 P	0.323	0.540	0.653 M	1.05
Foot and leg	Femoral condyles/medial malleolus	0.061 M	0.606	0.394 P	0.416	0.735	0.572 P	1.09
Total leg	Greater trochanter/medial malleolus	0.161 M	0.447	0.553 P	0.326	0.560	0.650 P	1.06
Head and neck	C7–T1 and 1st rib/ear canal	0.081 M	1.000	— PC	0.495	0.116	— PC	1.11
Shoulder mass	Sternoclavicular joint/glenohumeral axis	—	0.712	0.288	—	—	—	1.04
Thorax	C7–T1/T12–L1 and diaphragm*	0.216 PC	0.82	0.18	—	—	—	0.92
Abdomen	T12–L1/L4–L5*	0.139 LC	0.44	0.56	—	—	—	—
Pelvis	L4–L5/greater trochanter*	0.142 LC	0.105	0.895	—	—	—	—
Thorax and abdomen	C7–T1/L4–L5*	0.355 LC	0.63	0.37	—	—	—	—
Abdomen and pelvis	T12–L1/greater trochanter*	0.281 PC	0.27	0.73	—	—	—	1.01
Trunk	Greater trochanter/glenohumeral joint*	0.497 M	0.50	0.50	—	—	—	1.03
Trunk head neck	Greater trochanter/glenohumeral joint*	0.578 MC	0.66	0.34 P	0.503	0.830	0.607 M	—
Head, arms, and trunk (HAT)	Greater trochanter/glenohumeral joint*	0.678 MC	0.626	0.374 PC	0.496	0.798	0.621 PC	—
HAT	Greater trochanter/mid rib	0.678	1.142	—	0.903	1.456	—	—

Photo: The Shade Room

Supervised Learning in Biomechanics

Ground truth is not measured directly



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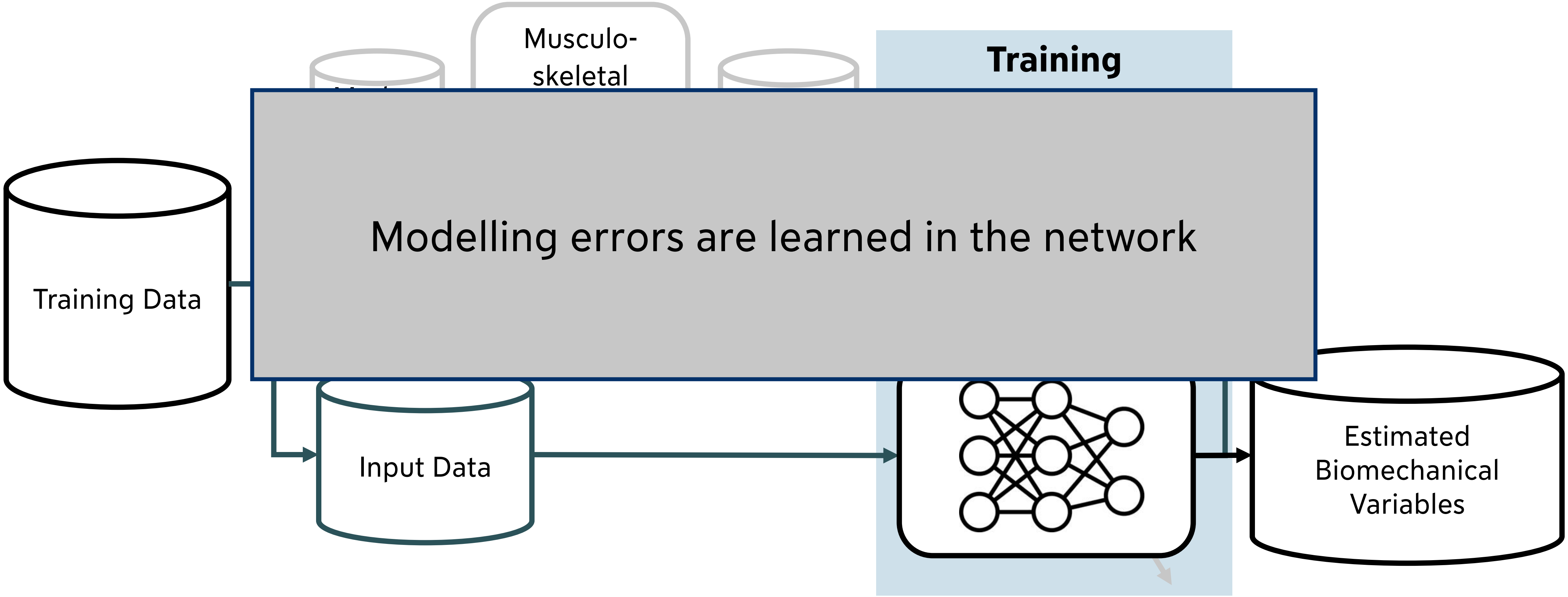


Modelling errors are learned in the network

Similarity of human movement

Creating a good model

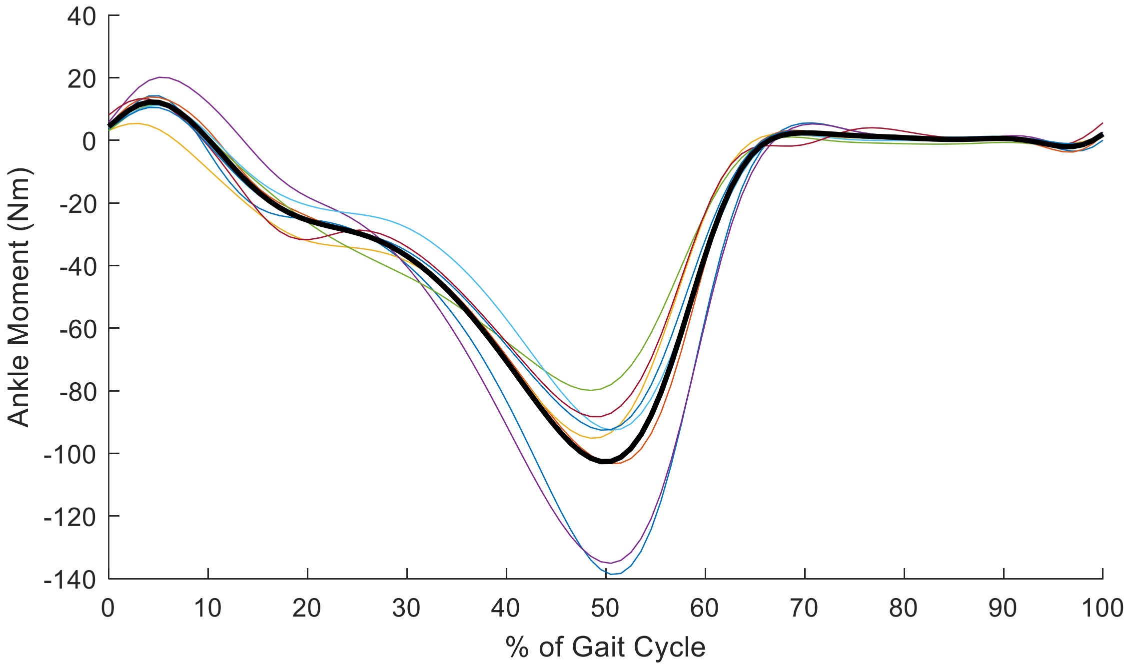
Data-based model to estimate joint moments

- Training data: walking at normal walking speed
- Output: mean of training data

Model performance

- Correlation: at least 0.98
- Normalized RMSE of less than 7%

→Similar to state-of-the-art neural network (e.g., Mundt et al., *Med Biol Eng Comput*, 2020)



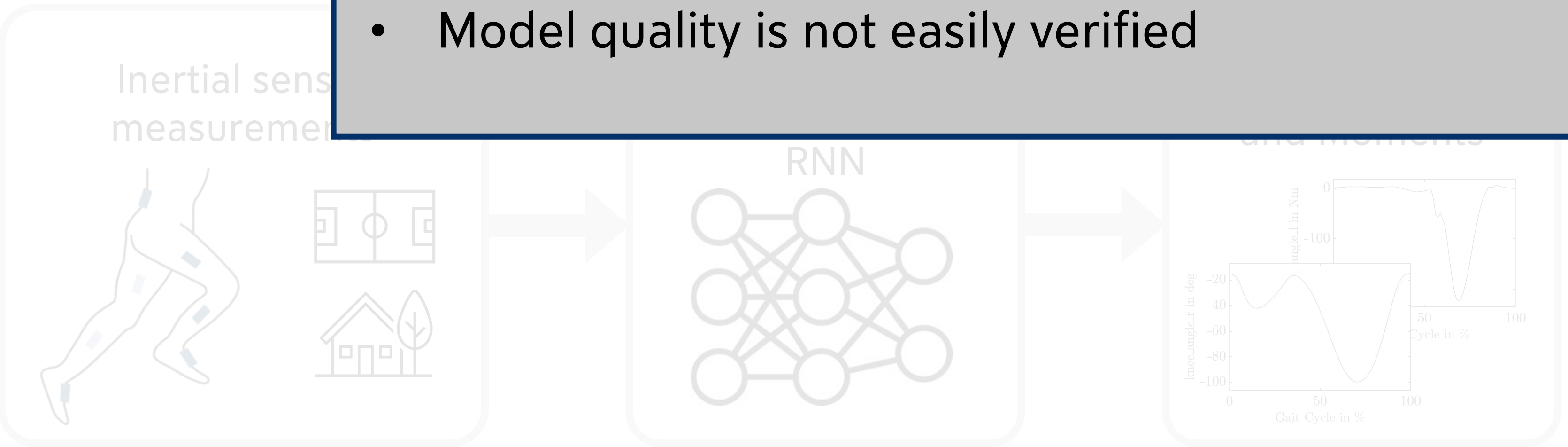
What defines good performance?

SSPINNpose

Machine Learning in Biomechanics

Self-Supervised Physics-Informed Neural Network

Pose and force



Machine learning for gait analysis is challenging

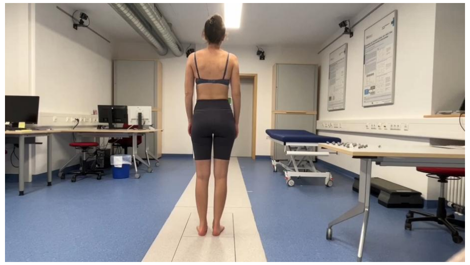
- Small datasets
- No direct ground truth
- Model quality is not easily verified

Gambietz et al., *ACM TIST*, in review

SSPINNpose

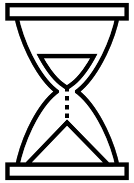
Machine Learning in Biomechanics

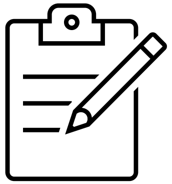
Self-Supervised



Physics-Informed

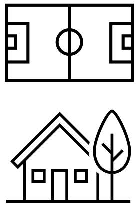
Neural Network





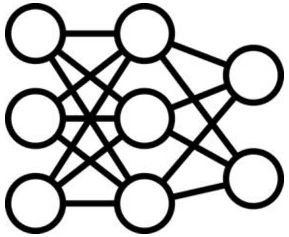
Pose and force estimations

Inertial sensor measurements



SSPINNpose

RNN



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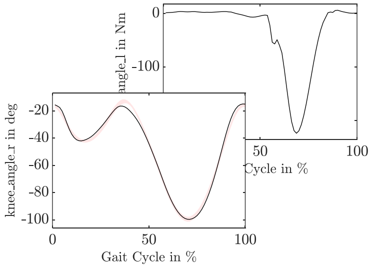
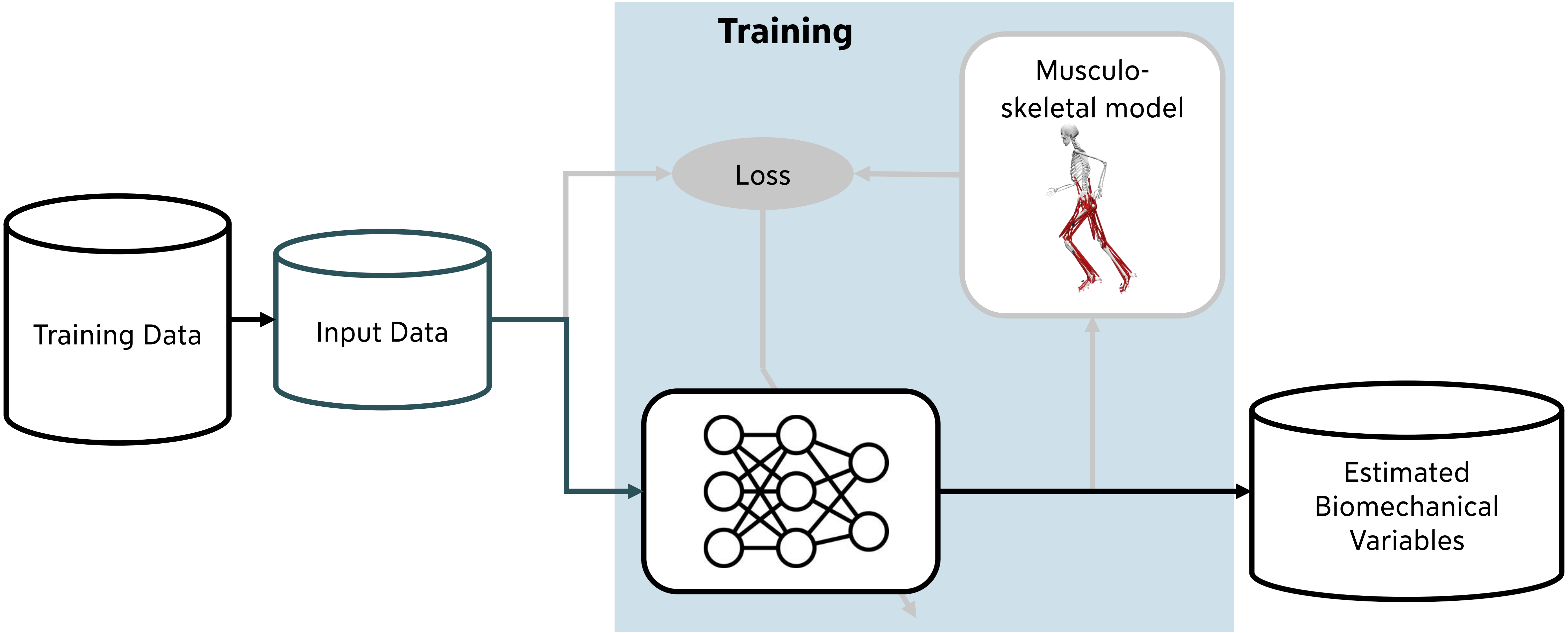


Gambietz et al., *ACM TIST*, in review

Self-Supervised Learning

No need for labelled ground truth



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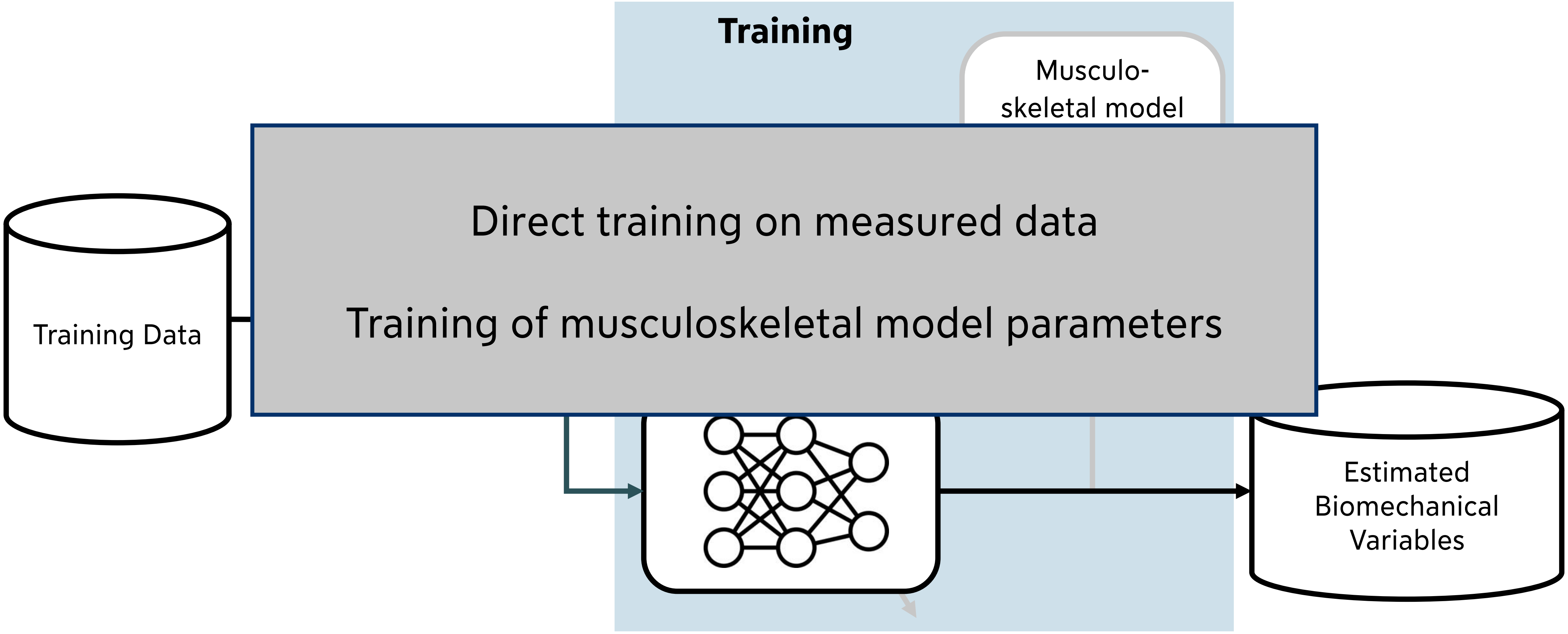
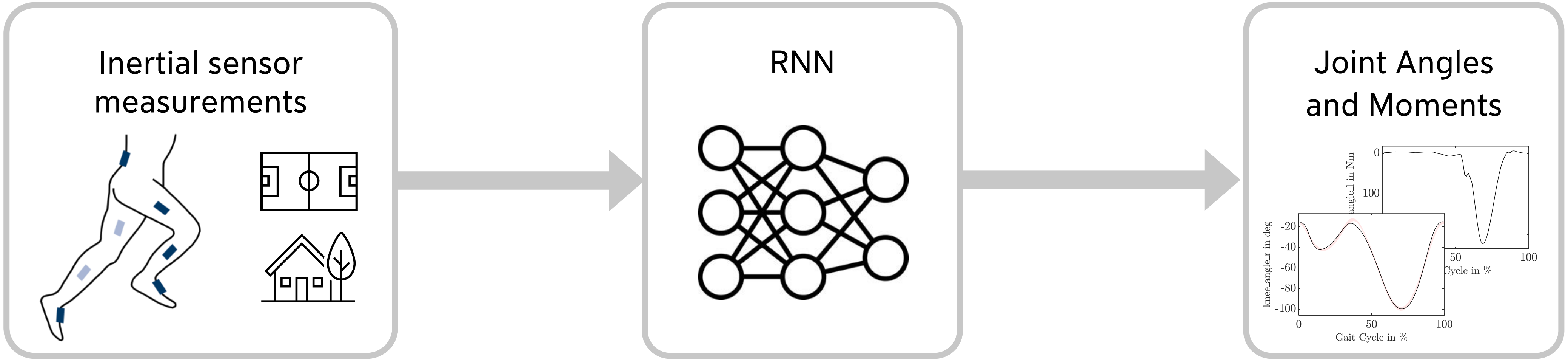


Direct training on measured data

Training of musculoskeletal model parameters

Methods

Recurrent Neural Network Design



Inputs at each time step:
- IMU measurements
  - Accelerations and velocities
- Body inertial parameters
- IMU location and orientation
- Ground contact parameters

Model architecture:
- Recurrent neural network
  - Long short-term memory (LSTM) network
  - Bi-directional LSTM
- Two dense layers

Outputs at each time step:
- Generalized coordinates, velocities and accelerations
- Joint torques
- Ground reaction forces
- Movement speed

Gambietz et al., *ACM TIST*, in review

Training Approach

Loss Function

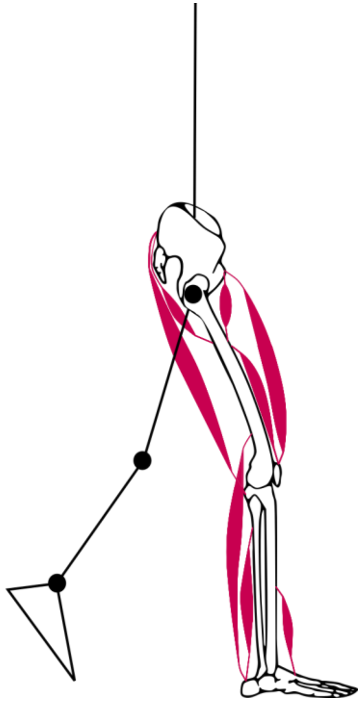
Three core losses

- Kane's loss $\mathcal{L}_K = (|F_r^* + F_r|)^2$ (Kane & Levinson, 1985)
  - Internal and external forces are in equilibrium: $|F_r^* + F_r| = 0$
- Temporal consistency loss $\mathcal{L}_T = \frac{x(n+1)-x(n)}{\Delta t} - v(n) = 0$
  - States in consecutive time points match velocities and accelerations
  - Solves exploding gradient problem
- IMU loss $\mathcal{L}_{IMU} = (s_{IMU} - \hat{s}_{IMU})^2$
  - Virtual IMU output matches measured IMU output

Auxiliary losses

- Physiology of movement: energy minimization
- Realism of movement

$$M(\boldsymbol{q})\ddot{\boldsymbol{q}} + C(\boldsymbol{q}, \dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + G(\boldsymbol{q}) = \tau + J(\boldsymbol{q})^T \boldsymbol{F}_{ext}$$



Gambietz et al., *ACM TIST*, in review

Experimental Dataset for Validation

Optical and Inertial Motion Capture

Recordings

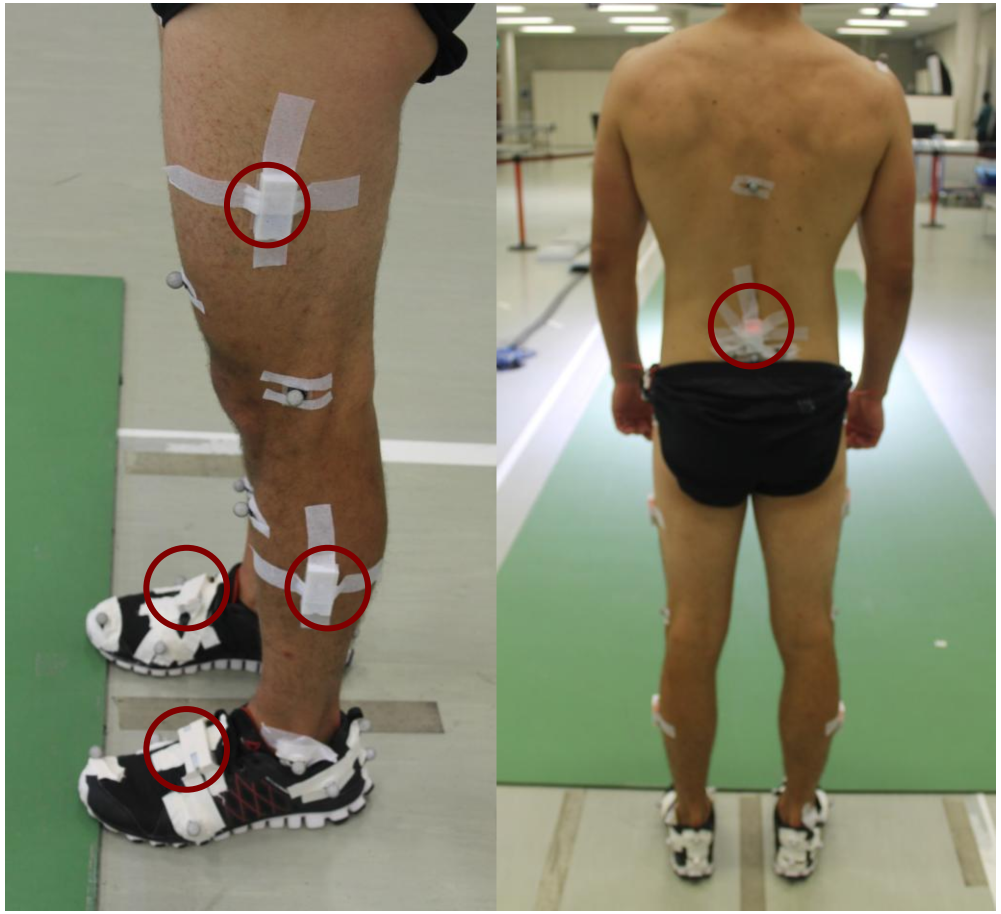
- 7 synchronized IMUs recording continuously
- Optical motion capture (ground truth) for a single stride

Conditions (0.9 - 4.9 m/s)

- Slow, normal and fast walking
- Slow, normal and fast running

Dataset

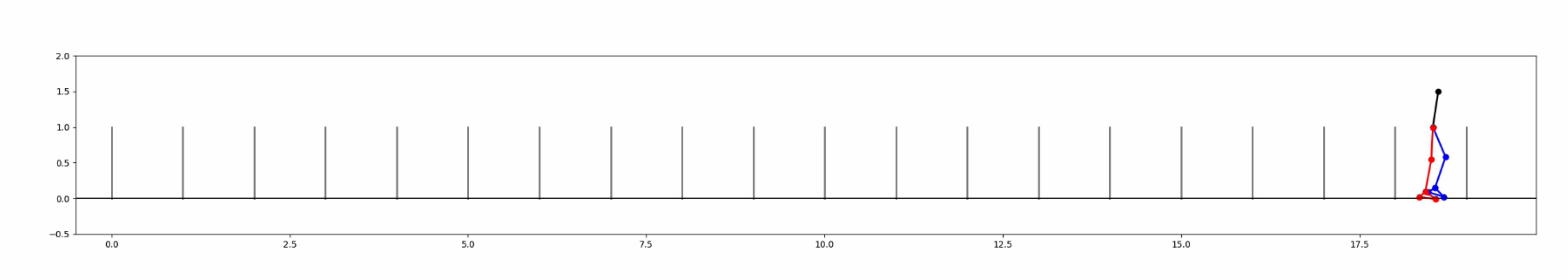
- 10 participants (182 ± 5 cm, 76.9 ± 8.6 kg)
- 76 minutes of suitable unlabelled IMU data
- Training on sequences of 256 time steps
- Testing on full sequences



Dorschky et al., *J Biomech*, 2019

Results

Motion Video

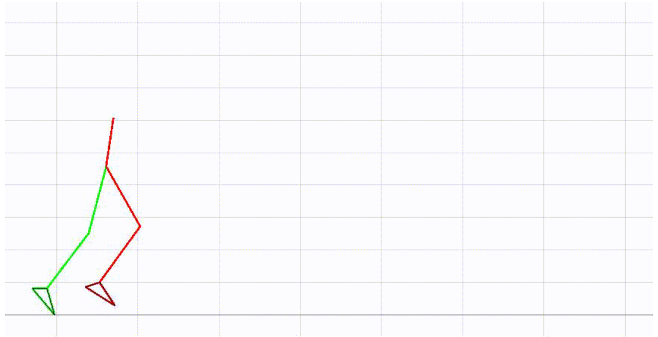


2D side view

- Sufficient for straight walking and running
- Extension to 3D possible

Reconstruction of multiple running steps

- So far, focus on single movement cycles captured with optical motion capture



Gambietz et al., *ACM TIST*, in review; Dorschky et al., *J Biomech*, 2019

Results

Error Metrics

Model	Need for labels	Latency	Joint angle error (deg)	Joint torque error (BWBH%)	Ground reaction force error (BW%)	Speed error (m/s)
SSPINNpose (LSTM)	No	3.5 ms	8.7	4.9	16.4	0.19
SSPINNpose (Bi-LSTM)	No	3.5 ms	8.9	5.0	18.8	0.15
CNN-based regression	Yes	<1 ms*	4.9	1.4	10.7	-
Optimal control	No	50 min	6.3	2.6	17.9	0.25

*inference only possible after full gait cycle

SSPINNpose

- is suitable for (near) real time inference in unrestricted environments
- leads to higher errors than state of the art
  - Same information available as in optimal control → possibility for improvement

Gambietz et al., *ACM TIST*, in review

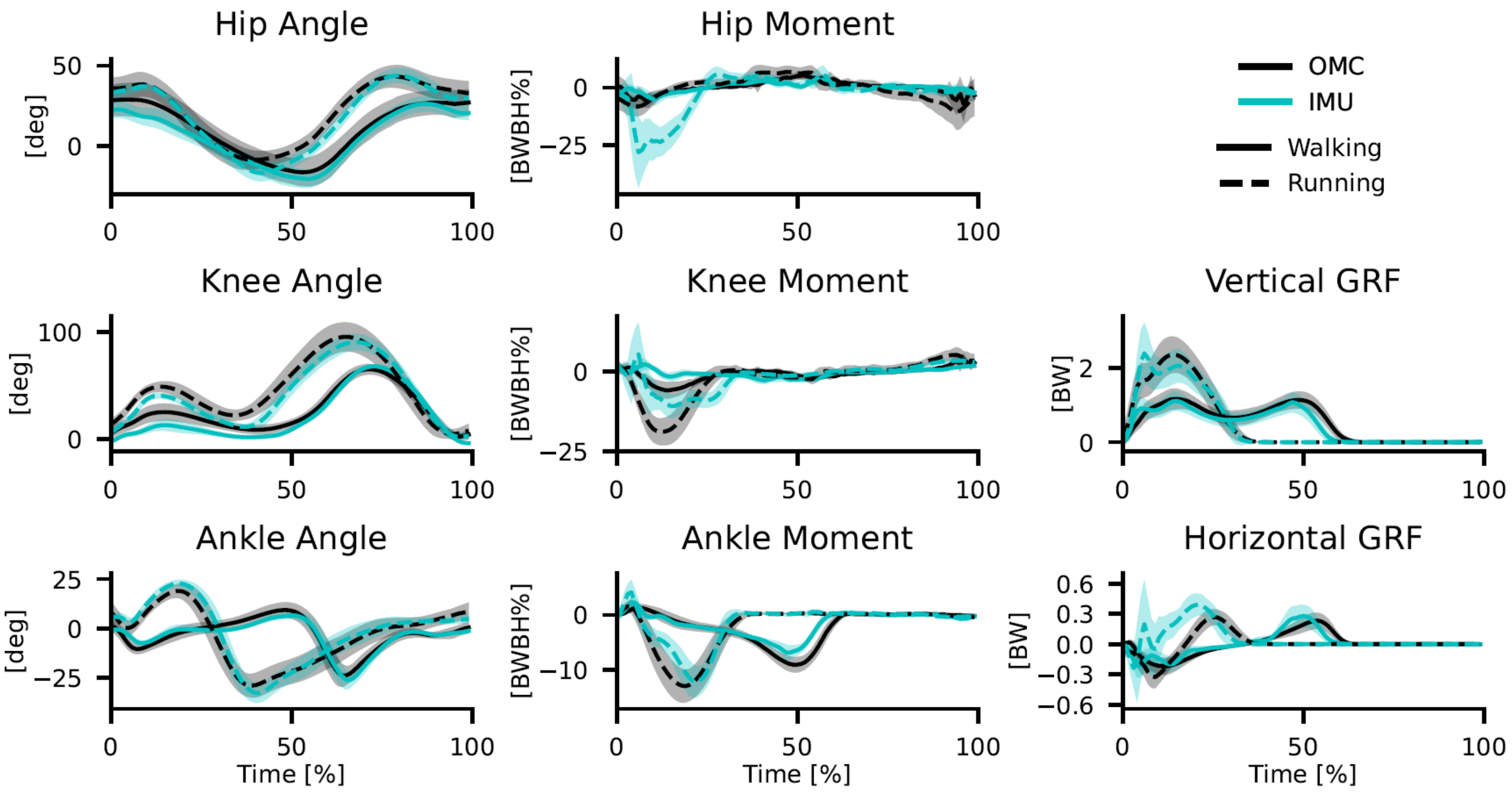
Results

Joint Angles and Moment Graphs

Joint angles are acceptable

Hip and knee moment deviate during stance

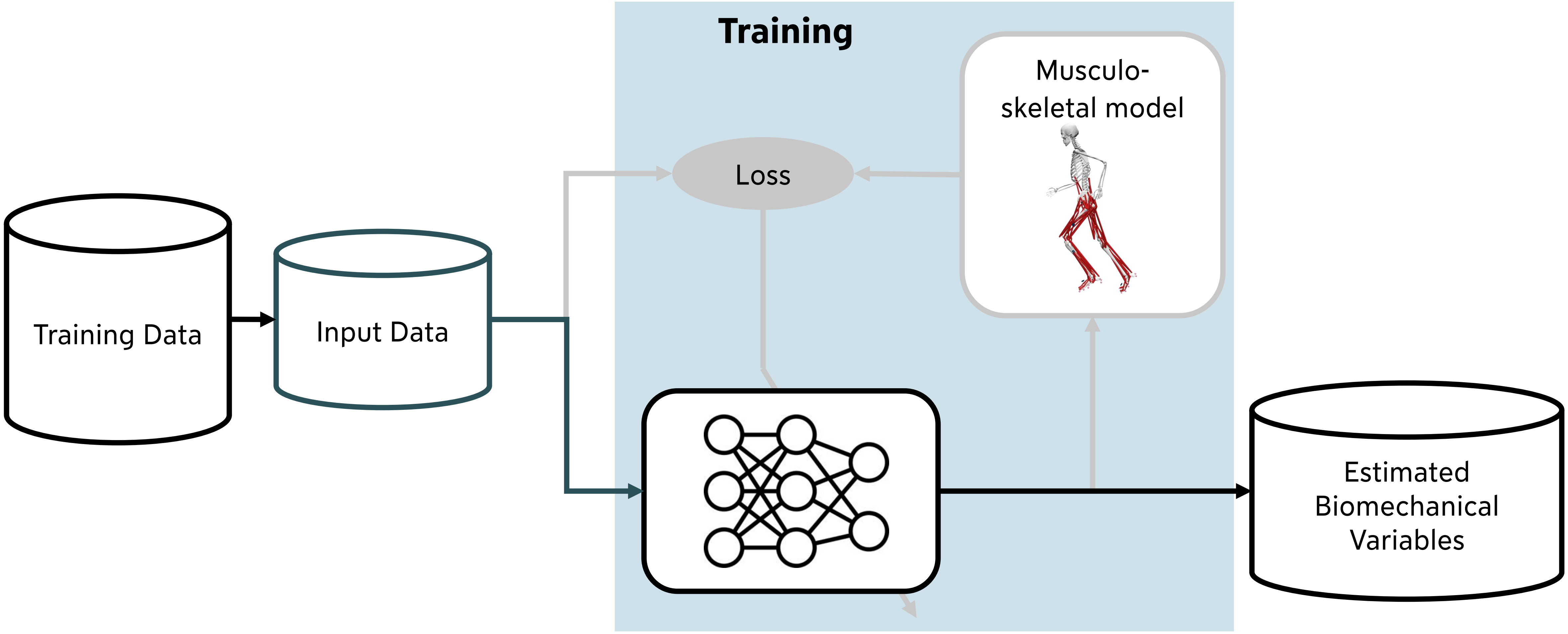
- Finetuning of Kane's loss
- Possible improvement by training of musculoskeletal model



Gambietz et al., *ACM TIST*, in review

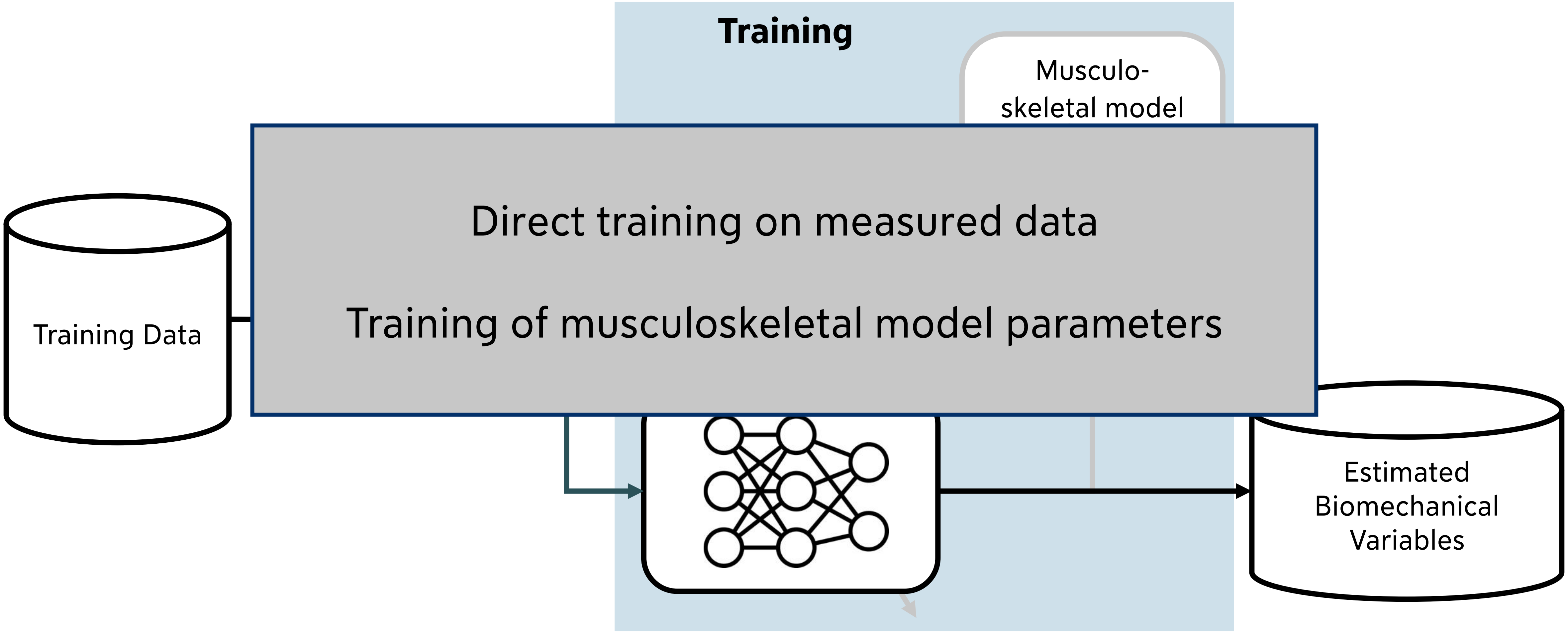
Self-Supervised Learning

No need for labelled ground truth



Self-Supervised Learning

No need for labelled ground truth

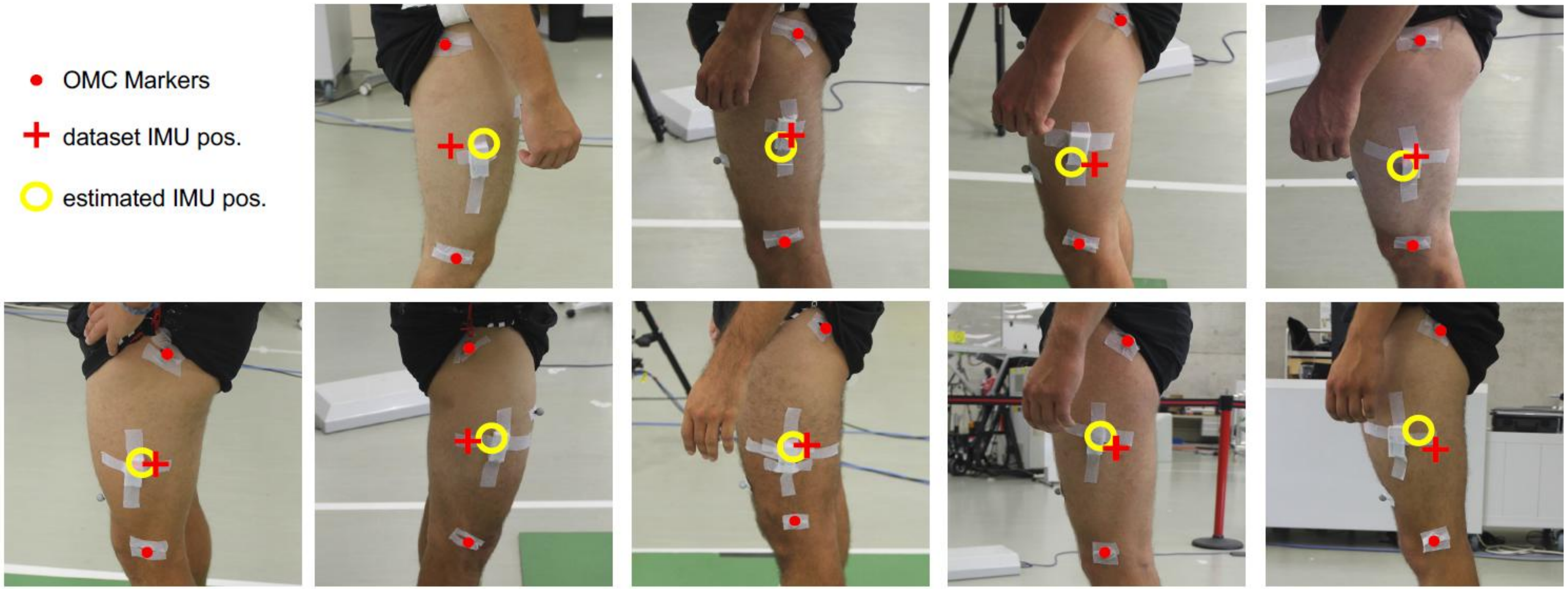


Direct training on measured data

Training of musculoskeletal model parameters

Training Virtual Sensor Model

Automatic Estimation of IMU Positions



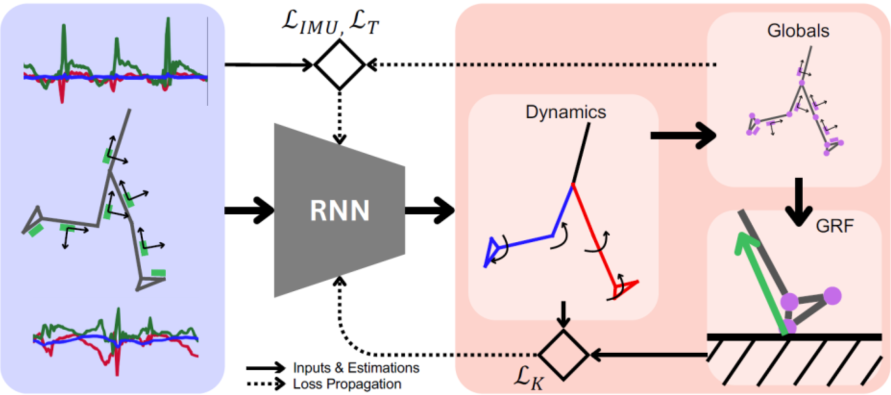
Successful personalization of IMU position

Important for usability

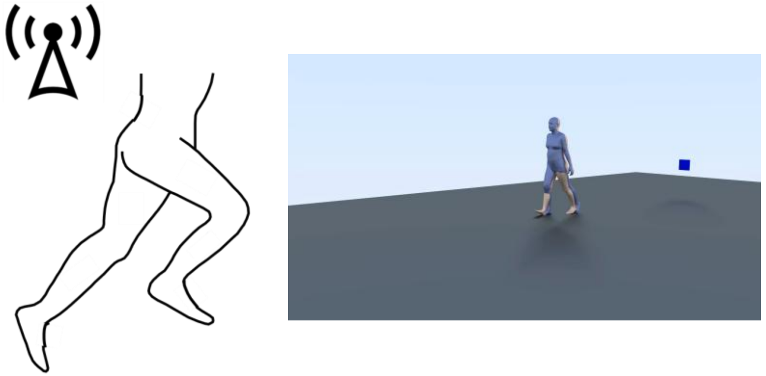
Gambietz et al., *ACM TIST*, in review

Future Work

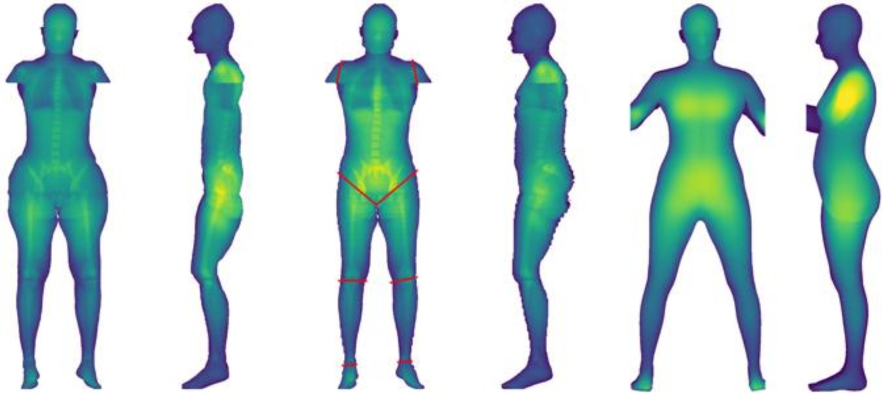
Validation and Improvements



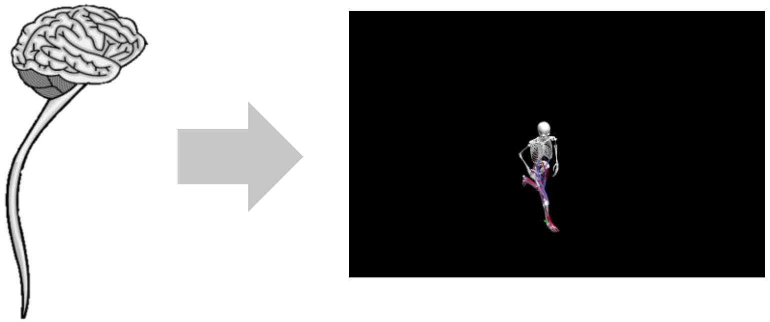
Performance improvement



Other sensors



MRI-based validation of personalization



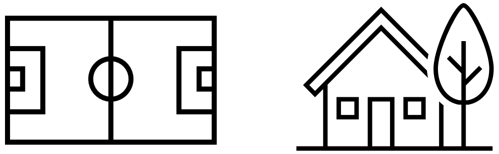
Predictions

Summary

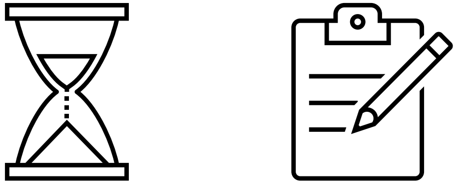
SSPINNpose Contribution

Through self-supervised physics informed training:

Movement recording anywhere



Direct feedback



Potential for personalized and specific outcomes

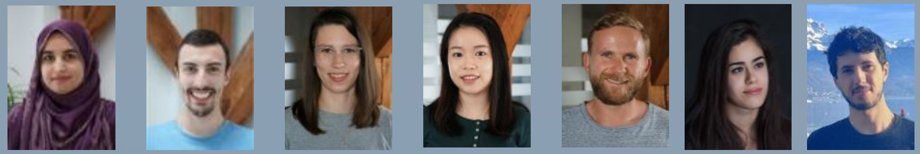
Diagnosis and Disease Monitoring

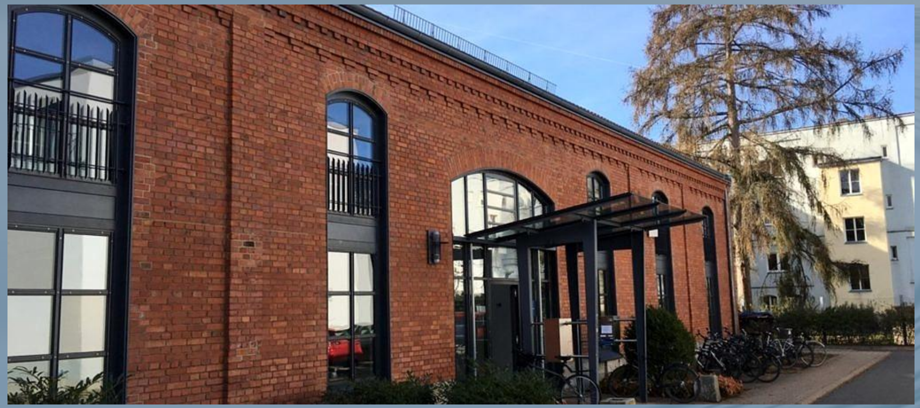
Performance Optimization

Device Optimization

Rehabilitation

BioMAC research group





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https://www.asm.tf.fau.de/en/startseite/research/biomac/