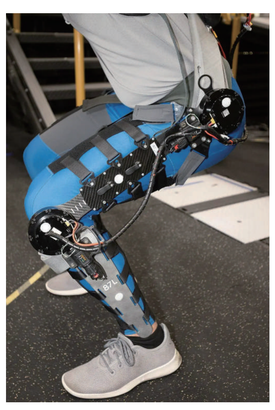
Optimizing Locomotor Task Sets for Training a Biological Joint Moment Estimator

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Motivation: Efficient Task-agnostic Hip Joint Moment Estimator



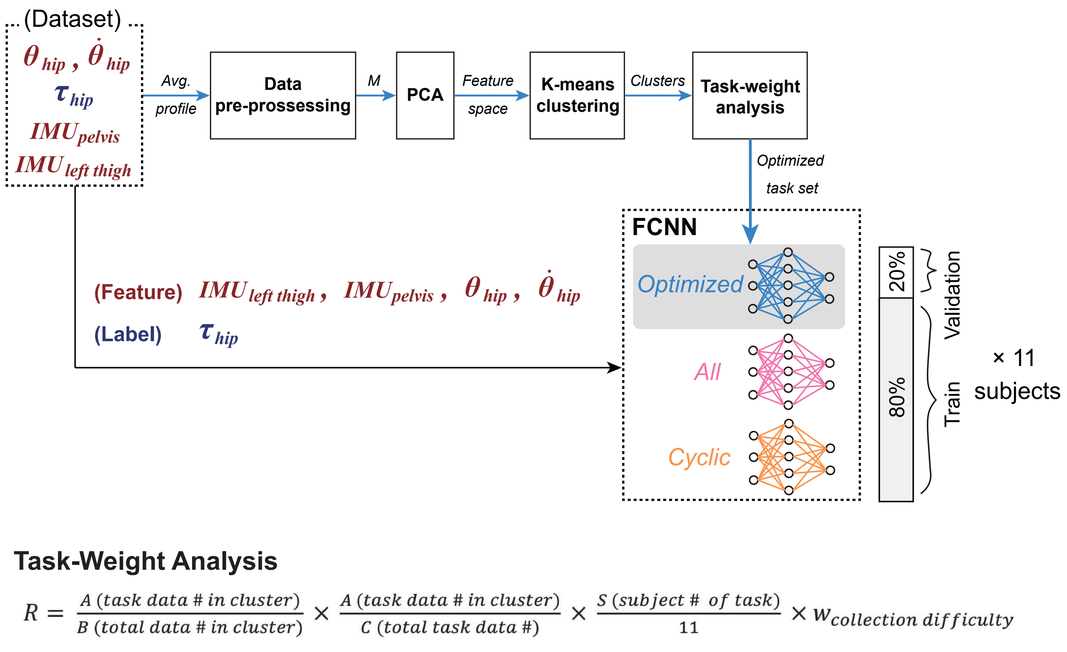


- Volitional, task-agnostic control of exoskeletons using instantaneous biological joint moment estimatior [1]

Challenges
- Deep-learning models demand extensive training data [2]
- No clear prioritization of locomotor tasks for biomechanical data collection

Aim: Train a task-agnostic hip joint moment estimator with a more data-efficient approach
- Characterize locomotor tasks with biomechanical features, and group tasks into similar tasks
- Select representative tasks from clusters and train the model

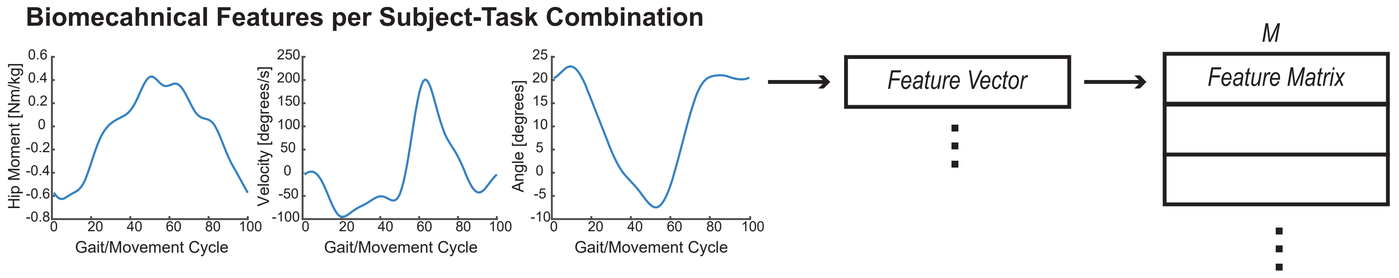
Methods



Task-Weight Analysis

$$R = \frac{A\ (task\ data\ \#\ in\ cluster)}{B\ (total\ data\ \#\ in\ cluster)} \times \frac{A\ (task\ data\ \#\ in\ cluster)}{C\ (total\ task\ data\ \#)} \times \frac{S\ (subject\ \#\ of\ task)}{11} \times w_{collection\ difficulty}$$

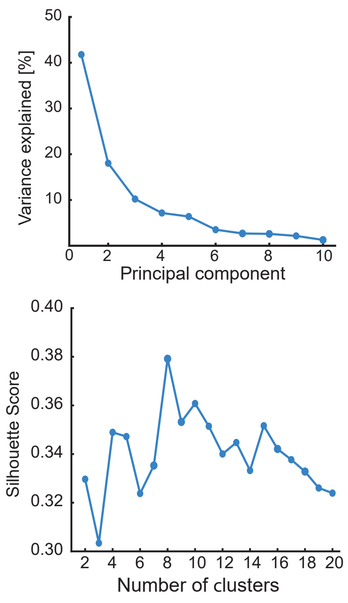
Biomecahnical Features per Subject-Task Combination



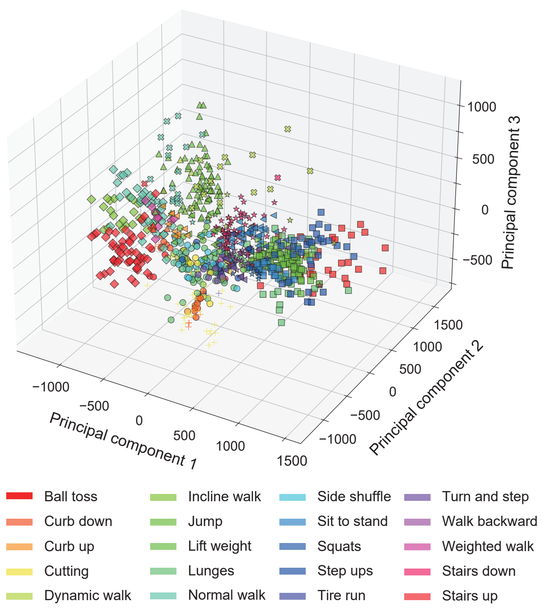
- Utilized an open-source biomechanical and wearable sensor dataset [3]
- Averaged hip joint angle, joint angular velocity, and joint moment profile per each task trial
- Dimensionality reduction via PCA + task grouping with k-means clustering
- Task-weight analysis for representative task selection and FCNN model training

Results

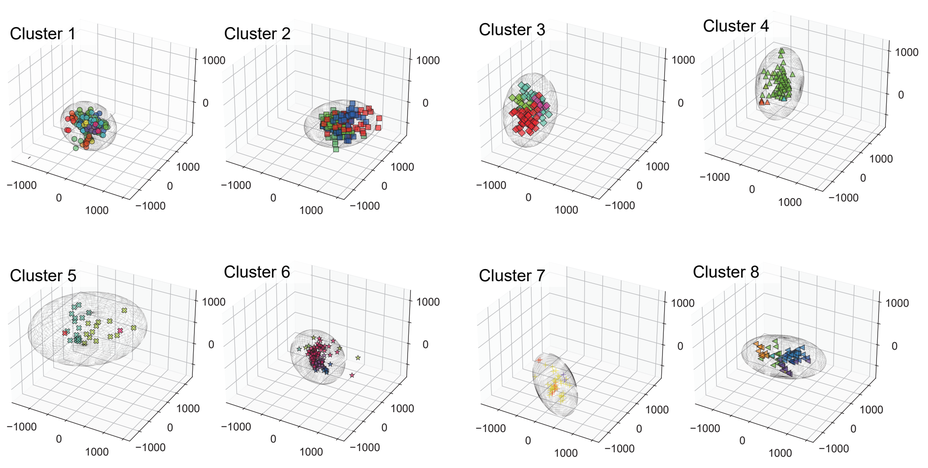
Variance and Sihouette Score



Reduced Feature Space



Clusters of Tasks



Representative Task Per Cluster

Clusters	Task	$\frac{A}{B}$	$\frac{A}{C}$	$\frac{S}{11}$	w	R
Cluster 1	Lunges	0.172	0.470	1.000	0.9	0.07280
	Dynamic Walk	0.128	0.523	1.000	0.9	0.06011
	Tire Run	0.122	1.000	1.000	0.9	0.11000
Cluster 2	Lift Weight	0.406	0.977	1.000	0.8	0.31715
	Lunges	0.165	0.530	1.000	0.9	0.07880
	Ball Toss	0.151	0.941	1.000	0.8	0.11365
Cluster 3	Stairs Up	0.438	0.914	0.909	1.0	0.36387
	Normal Walk	0.298	0.493	1.000	1.0	0.14672
	Incline Walk	0.182	1.000	1.000	1.0	0.18182
Cluster 4	Jump	0.906	0.755	1.000	0.9	0.61547
	Curb Down	0.047	0.167	0.273	0.8	0.00171
	Dynamic Walk	0.024	0.045	0.182	0.9	0.00018
Cluster 5	Normal Walk	0.531	0.233	0.727	1.0	0.08998
	Dynamic Walk	0.406	0.295	0.818	0.9	0.08838
	Stairs Down	0.031	0.017	0.091	1.0	0.00005
Cluster 6	Stairs Down	0.528	0.950	0.909	1.0	0.45581
	Walk Backward	0.287	0.939	1.000	0.9	0.24268
	Dynamic Walk	0.056	0.136	0.364	0.9	0.00248
Cluster 7	Cutting	0.686	0.795	1.000	0.8	0.43672
	Curb Down	0.137	0.292	0.455	0.8	0.01456
	Curb Up	0.137	0.292	0.545	0.8	0.01747
Cluster 8	Sit to Stand	0.393	0.500	1.000	0.9	0.17679
	Jump	0.167	0.137	0.727	0.9	0.01497
	Turn and Step	0.143	0.600	1.000	0.8	0.06857

- Only 8 out of 20 tasks chosen as optimized tasks
- Significantly outperformed the cyclic tasks model (20% less error)
- Comparable to the all-tasks model

RMSE and R2

Estimation and Ground Truth Hip Moment

- **This study demonstrates that distinct locomotor tasks can be effectively grouped based on their underlying biomechanical features.**
- **Furthermore, the deep learning model is capable of capturing inter-task similarities and performing in a task-agnostic manner, without requiring extensive data collection and training process.**

Future works

Incorporate **more diverse biomechanical and physiological measures** for inter-tasks relationship (e.g. muscle activation level during locomotion)

Integrate the task clustering strategy to the high-level control layer to achieve **optimal task-agnostic exoskeleton assistance**

References

[1] D. D. Molinaro et al., "Task-agnostic exoskeleton control via biological joint moment estimation", Nature. 2024;635(7613):337–344.
[2] K. L. Scherpereel et al., "Improving Biological Joint Moment Estimation During Real-World Tasks With EMG and Instrumented Insoles", IEEE Trans Biomed Eng. 2024;71(9):2718–2727.
[3] K. L. Scherpereel et al., "A human lower-limb biomechanics and wearable sensors dataset during cyclic and non-cyclic activities", Sci Data. 2023;10:924.

Links

Paper

Project Webpage