A GENERATIVE DEEP LEARNING MODEL PREDICTS GROUND REACTION FORCES AND FUTURE KINEMATICS

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Introduction: Deep learning models can predict 3-D gait kinematics and kinetics from sparse kinematics measurements [1]. However, such models require large datasets for training, a rarity in the biomechanics field where datasets typically contain a small number of subjects tested in a single laboratory. We recently created a large human dynamics dataset using the AddBiomechanics tool [2], which standardized marker-based motion capture data and ground reaction force (GRF) data from fifteen studies conducted by twelve different laboratories. Our dataset has more than 50 hours of gait dynamics data collected from 273 subjects, mitigating the biases of individual datasets. We used our large dataset to train a diffusion-based, general-purpose generative model, which represents human gait dynamics and can generate unknown biomechanical parameters that are harmonious with known ones. As such, unlike prior regressive deep learning models that have strict specifications regarding inputs and outputs, our model allows flexible input-output pairs, thus adaptable to various prediction tasks. In this abstract, we present the performance of our unified generative gait model on three example tasks: 1) predicting GRF using kinematics, 2) predicting future lower-limb joint angles using past kinematics, and 3) reconstructing pelvis and trunk kinematics using lower-limb kinematics.

Methods: The AddBiomechanics dataset was split into training and test sets. The test set consists of walking and running gait data for fifteen randomly selected subjects (one from each of the fifteen constituent datasets); the remaining subjects' data, regardless of motion type, were used for training. The motion states in each trial (i.e., kinematics of an OpenSim Rajagopal model [3] and 3-D body weight (BW) normalized GRF of each foot) were linearly resampled to 60 Hz and randomly segmented into 1.5s windows, creating 2-D matrices with dimensions of time and states. We added iteratively increasing noise into each data window and trained a transformer-based generative model to recognize the noise [4]. This trained model was used for all three downstream prediction tasks during testing. For each task, the portion of the data windows corresponding to the desired model output was masked by random noise whereas the input portion was preserved. Then, the model used the input portion as guidance to remove noise from the output. The unmasked inputs for the three tasks were: 1) full-body kinematics of all the time steps, 2) full-body kinematics of the first 1,480ms, 1,460ms, …, and 1,300ms of each 1.5s window, and 3) combinations of lower-limb joint angles (Table 2) of all the time steps. For each constituent dataset, its average GRF and kinematics curves across all the gait cycles were used as the baseline. Specifically, gait cycles of the training set were segmented based on GRF, resampled to 100 points, averaged, and resampled to match the lengths of test set gait cycles.

Table 1: RMSE of GRF Estimation When Using Full-Body Kinematics as Model Input.

Axis		RMSE (BW)
Medio-lateral GRF	Baseline	0.27 ± 0.07
	Proposed	**0.22 ± 0.06**
Anterior-posterior GRF	Baseline	0.46 ± 0.16
	Proposed	**0.32 ± 0.13**
Vertical GRF	Baseline	2.18 ± 1.25
	Proposed	**1.16 ± 0.64**

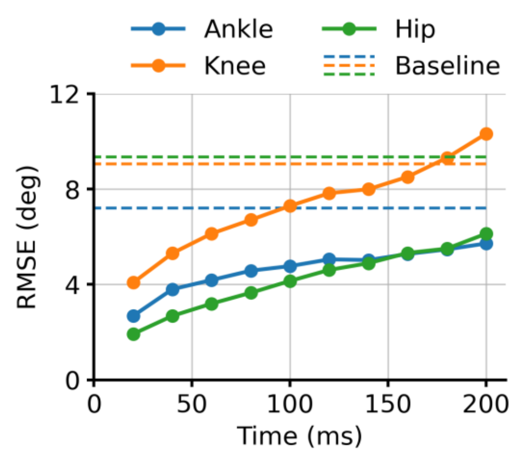

Figure 1: RMSE of Future Ankle, Knee, and Hip Flexion Angle Prediction When Using the Past Full-Body Kinematics as Model Input. Predictions were made from 20 ms to 200 ms ahead of the input.

Results & Discussion: For GRF prediction, our model outperformed the baseline across all three axes (Table 1). For future joint angle prediction, our model outperformed the baseline for predicting motion states up to 160ms in the future (Figure 1). By providing different inputs to the model, we observed the need for 3-D Hip angles to reconstruct pelvis and trunk angles with maximal accuracy, compared to solely using ankle and knee flexion angles (Table 2).

In summary, our deep-learning-based gait model trained on a large biomechanics dataset outperformed the baseline across multiple tasks, including GRF prediction, future kinematics prediction, and missing kinematics reconstruction. Unlike previous models, our model is adaptable to a range of input combinations and prediction targets due to its generative nature.

Table 2: RMSE of Pelvis and Trunk Kinematics Reconstruction When Using Combinations of Joint Angles as Model Input.

Input			RMSE
Ankle Flexion	Knee Flexion	3-D Hip	
✓			8.03 ± 4.16
	✓		8.03 ± 4.09
✓	✓		7.44 ± 3.93
		✓	4.74 ± 3.19
✓	✓	✓	**3.76 ± 2.32**
Baseline			5.07 ± 2.64

Significance: Our general-purpose generative gait model can be used to predict current and future kinematics and kinetics, thus potentially enabling applications such as exoskeleton control and gait training.

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References: [1] Zago et al. (2021), *Front. Bioeng. Biotechnol.* 638793; [2] Werling et al. (2023), *Plos One* 18(11); [3] Rajagopal et al. (2016) *IEEE TBME* 63(10); [4] Van Wouwe et al. (2023), arxiv:2308.16682