Supplementary Material: Physics-Augmented Autoencoder for 3D Skeleton-Based Gait Recognition

Hongji Guo and Qiang Ji
Rensselaer Polytechnic Institute, Troy, NY 12180
{guoh11, jiq}@rpi.edu

1. Details of The RNN-Based Classifier

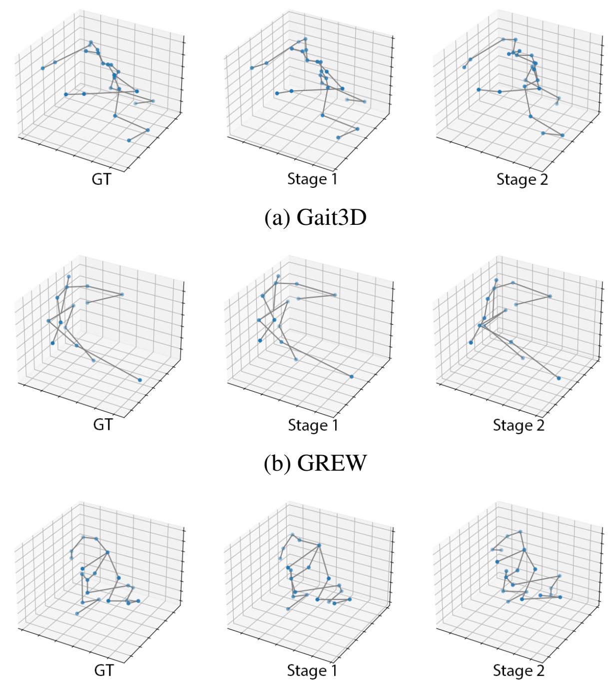
To perform the gait recognition, we use a recurrent neural network (RNN) as the classifier. It takes the generalized positions and forces of joints at each frame as the input. At each frame, we concatenate the joint positions $\mathbf{q}_t \in \mathbb{R}^D$ and forces $\mathbf{f}_t \in \mathbb{R}^D$ to form the feature vector $\mathbf{W}_t \in \mathbb{R}^{2D}$, where D is the total degree-of-freedom of all joints. The feature vector is projected by two linear layers before being fed into the RNN. We set the hidden size or the RNN as 1024 and we stack 5 RNN layers. A dropout layer with rate 0.1 is applied on the outputs of each RNN layers except the last layer. We choose $tanh$ as the non-linearity activation function. The bidirectional parameter is set to False since we aim to capture the physical dynamics of the gait process in a time-forward manner.

2. Experiment Results on OUMVLP

We also evaluated our proposed PAA on OUMVLP dataset [1]. We used the provided 3D human poses with 24 joints extracted from human meshes. The experiment results with different settings are shown in Table 1. Our proposed PAA achieved strong results on this dataset. The results also demonstrate the effectiveness of our proposed physics modeling mechanism.

Encoder type	Decoder type	R-1 (%)	R-5 (%)
RNN	RNN	45.74	52.68
GCN	GCN	51.26	64.94
RNN	Physics-based	53.10	67.59
GCN	Physics-based	**59.46**	**73.92**

Table 1: **Results on OUMVLP.**



(a) Gait3D

(b) GREW

(c) KinectGait

Figure 1: **Failure cases of skeleton reconstruction.** Some skeletons are not well reconstructed after training stage 2.

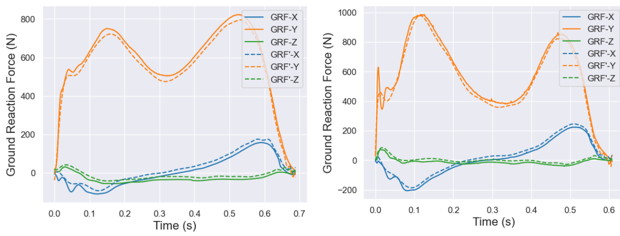
3. Additional Qualitative Results

3.1. Force prediction

Here we provide more visualizations of the force prediction on [2]. To better study the physical plausibility of the prediction, we applied PAA on different walking tasks. Specifically, the gait sequences of [2] have different walking tasks including normal walking, heel walking, toe walking, stepping up, and stepping down. We visualize the ground reaction force prediction of each walking task as well as failure cases in Figure 2.

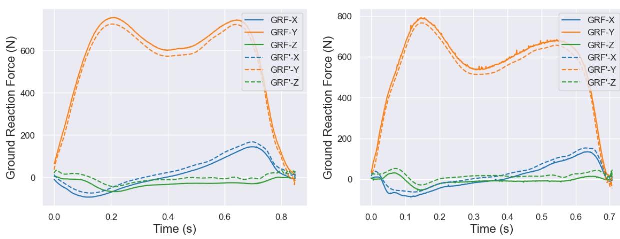
3.2. Skeleton reconstruction

Here we include more skeleton reconstruction results. The skeletons of Gait3D, GREW, and KinectGait are shown in Figure 3, 4 and 5 respectively. Most Skeletons are well reconstructed. Some failure cases are shown in Figure 1.

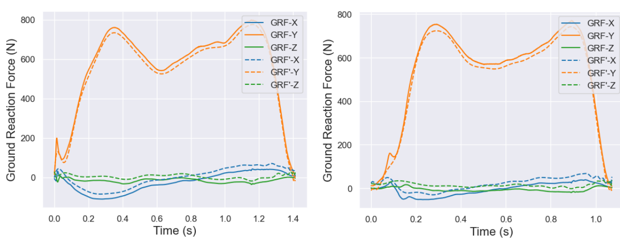


(a) Normal walking.

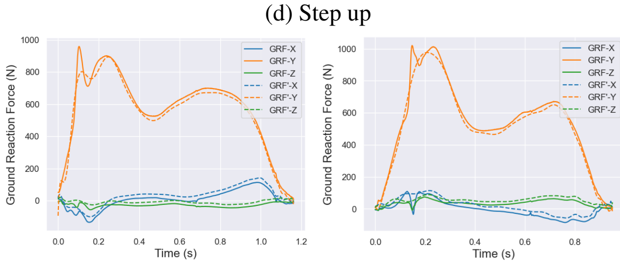
(b) Heel walking.



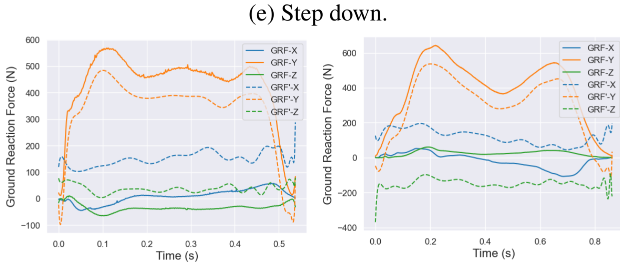
(c) Toe walking.



(d) Step up



(e) Step down.



(f) Failure cases

Figure 2: **Force prediction for different walking tasks.**

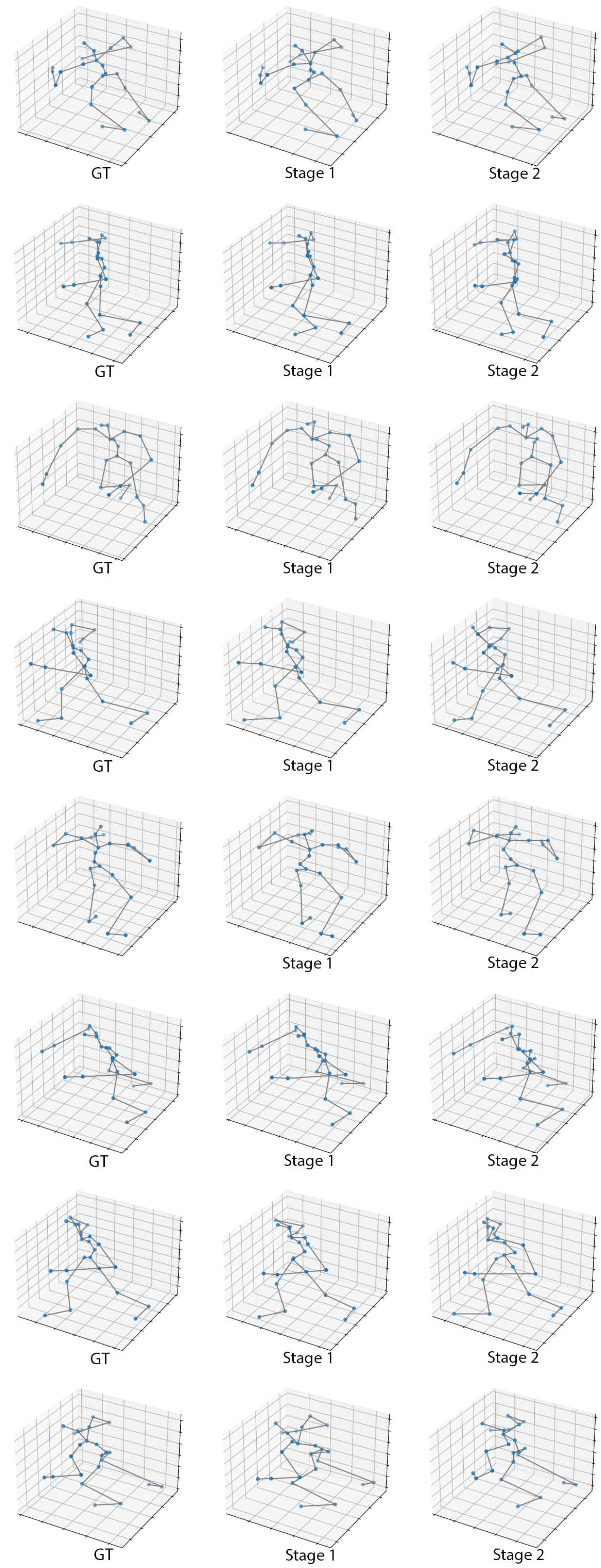


Figure 3: **Gait3D skeletons.**

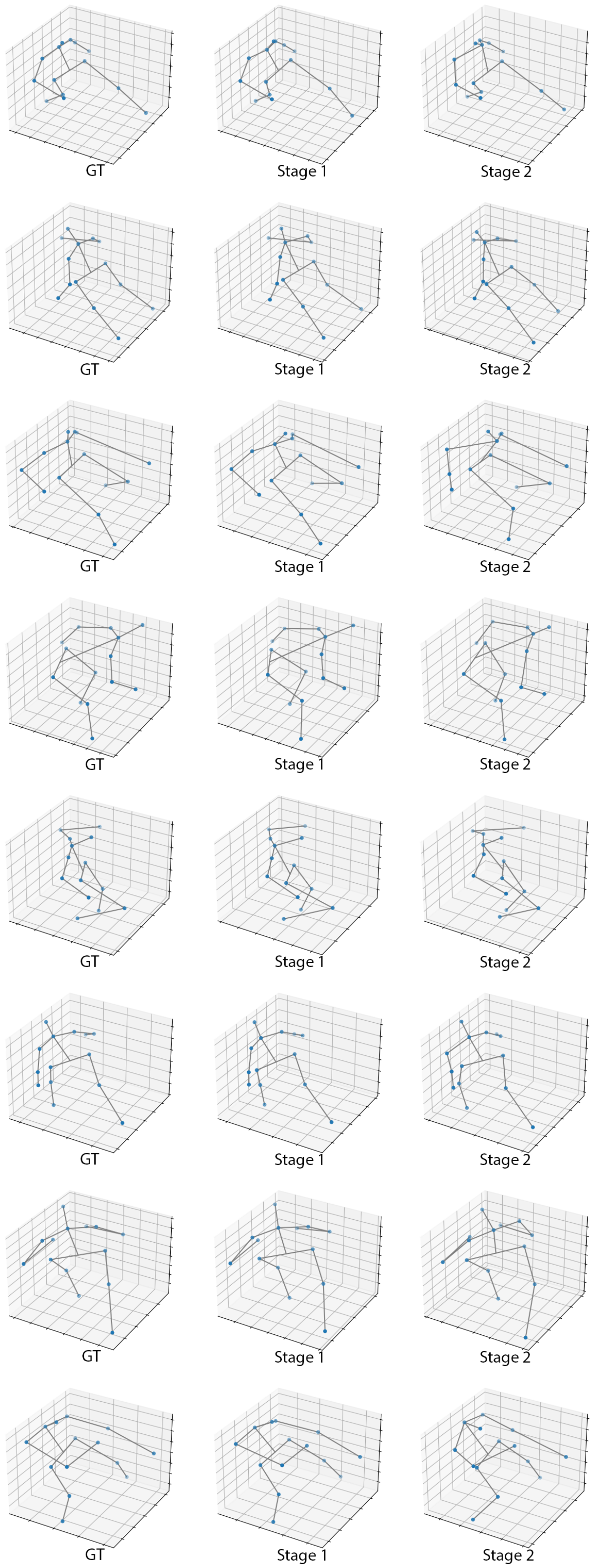


Figure 4: **GREW skeletons.**

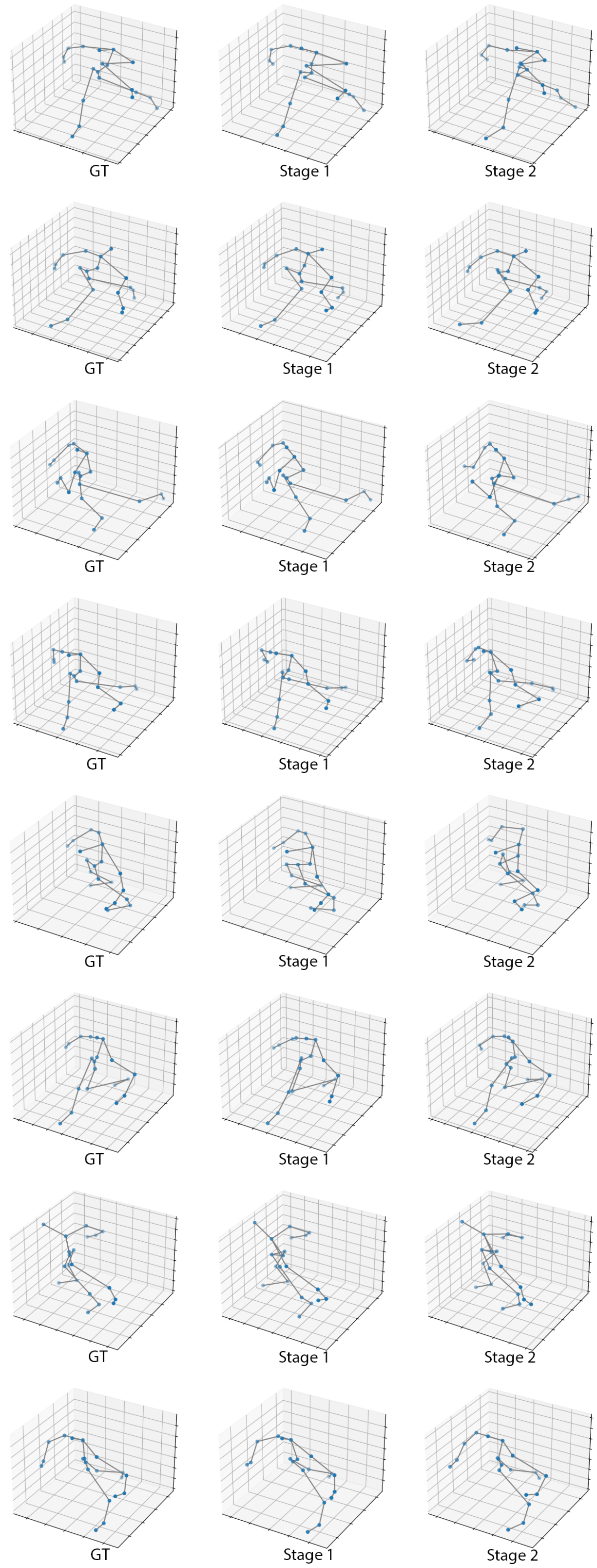


Figure 5: **KinectGait skeletons.**

References

[1] Weizhi An, Shiqi Yu, Yasushi Makihara, Xinhui Wu, Chi Xu, Yang Yu, Rijun Liao, and Yasushi Yagi. Performance evaluation of model-based gait on multi-view very large population database with pose sequences. *IEEE transactions on biometrics, behavior, and identity science*, 2(4):421–430, 2020. 1

[2] Tiziana Lencioni, Ilaria Carpinella, Marco Rabuffetti, Alberto Marzegan, and Maurizio Ferrarin. Human kinematic, kinetic and emg data during different walking and stair ascending and descending tasks. *Scientific data*, 6(1):309, 2019. 1