Population-based Generative Gait Controller for Forward Dynamics Simulation

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Summary

A gait controller as a single neural network was developed to simulate human walking across diverse body scales and gait styles using reinforcement learning. The model incorporates subject-specific scale factors and gait codes, achieving a mean absolute error of 3.4° for hip flexion.

Introduction

Forward dynamics simulation can be utilized for predictive biomechanical simulations to explore the effect of external forces on the kinematics and kinetics of joints and muscles. Recent advances in deep reinforcement learning enabled neural-network-based gait controllers in forward dynamics simulation to reproduce measured kinematics. Meanwhile, training the controller requires far more computation than inverse dynamics [1]. Optimizing controllers for each person to simulate a large population becomes impractical though generalization across diverse body scales and walking styles is important. This study aims to simulate human models with varying body scales and walking styles with a single neural network controller. The controller receives scale factors and gait codes, which encode each person's unique walking style. We hypothesize that the controller can generate more accurate motion for a specific person when the corresponding scale and gait code are given, compared to the random inputs.

Methods

From the data of 120 male subjects aged 20-60, body scales and gait kinematics of five cycles per subject were calculated using OpenSim. Kinematics consists of 28 coordinates from a 31-DOF skeletal model, excluding base translation. A gait cycle was temporally normalized to 100 frames, resulting in a 2800D vector. Two variational autoencoders were trained to encode the kinematics [2]. The cycle encoder encodes the 2800D vectors to capture the kinematic characteristics of an entire gait cycle. The pose encoder encodes 28D vectors at each timestep, given speed, period, and gait phase. The mutual information between codes from the cycle and pose encoders was maximized [3], producing a two-dimensional gait code from the pose encoder that captures the phase-invariant style features of each person (Figure 1a).

The skeletal model in RaiSim dynamics solver is randomly scaled based on the dataset (Figure 1b). The neural network to control the model with torques was trained with DRL. The state includes the current kinematics, scale factors, and gait code. The reward calculated from the pose encoder evaluates two aspects: how well the motion matches the dataset; and how well the motion retains the input style.

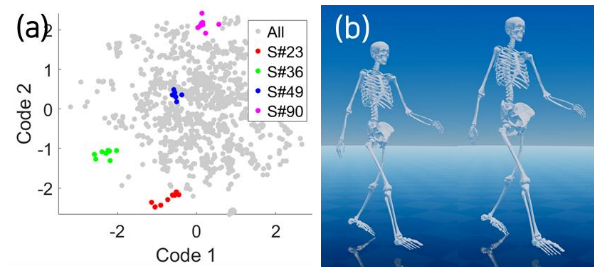

Figure 1: (a) Gait codes of four subjects from pose encoder. (b) Human skeletal model with various scales.

Results and Discussion

The proposed gait controller generated kinematics closely matching the dataset distribution and expressed the unique style of each subject (Figure 2). For all the subjects, the mean absolute error (MAE) of right hip flexion with random inputs (scale factor, gait code, speed, and period) was 7.6°, while the MAE with subject-specific inputs was reduced to 3.4°. For comparison, a recent study using DeepMimic [4] reported a 2.7° error in hip flexion [5]. Our accuracy was comparable to DeepMimic while DeepMimic is limited to learning a single or a few motion clips at a time.

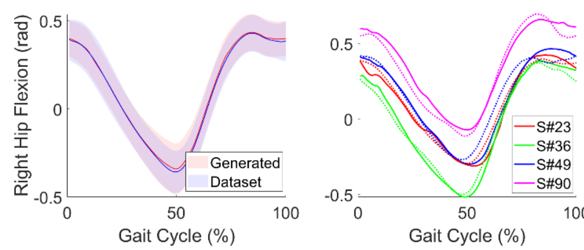

Figure 2: (a) Right hip flexion distributions of randomly generated motion and the dataset. (b) Right hip flexion of four subjects from simulation (solid line) and dataset (dotted line).

Conclusions

This study demonstrated motion generation with diverse body scales and gait styles with a single neural network. The population-level simulation will benefit research in human movement biomechanics and assistive technologies.

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