The effect of noise injection method on DRL-based controller robustness of human gait model

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***Abstract*— Human gait models in the dynamic environment have been studied to understand the fundamental neuronal control system of the human. Previously, imitation learning methods with reinforcement learning could successfully reproduce human gait motions using skeletal models. However, imitation learning-based controllers could have lacks of the ability to flexibly adapt to a wide range of state spatial scenarios such as instabilities and falling. Recently, noise injection methods have been introduced to increase the flexibility and robustness of the controller for robot systems. Therefore, the objectives of this study were to train human gait controllers with the noise injection method and to analyze the effect of noise injections on the balance recovery against external forces. A three-dimensional skeletal human gait model and two gait controllers with and without noise injections were developed. The robustness of the gait controllers against external forces was tested via forward dynamics-based gait simulation. The number of simulations without falling against external forces increased when the gait controller was trained with the noise injection method. In this study, the noise injection method during imitation learning could enhance the robustness and stability of the human gait controller.**

Keywords—Deep reinforcement learning, Imitation learning, Human gait model, Forward dynamics simulation, Controller robustness

I. INTRODUCTION

Human gait model simulations in the dynamics environment have been studied to understand the fundamental neuronal control system of the human [1], biomechanical pathologies of neuro-musculoskeletal diseases [2], and the effect of human-assistive devices [3]. In the forward dynamics environment, the locomotion of human models could be simulated using gait controllers [1]. The gait controllers were modeled by reflecting the neuronal control system of the human [1, 4]. The neuronal control system of the human consists of afferent signals (sensory signals) and efferent signals (motor signals) [5]. As such, the gait controllers generated motor control signals such as torque and muscle actuation from sensory signals of dynamic states including joint angles and posture of human gait models [4]. However, the development of gait controllers reflecting the complexity of the neuronal control system of the human is still challenging.

Recently, it has become possible to develop controllers of complex systems such as multi-degree-of-freedom robots due to the progression of artificial intelligence [6]. Deep reinforcement learning methods have been used to develop controllers for locomotion of the humanoid and quadrupedal robots [6]. Especially, imitation learning (IL) methods that trained the controllers to track the reference motions were introduced to implement human-like locomotion [7]. Previously, the IL methods could successfully reproduce walking motions using a skeletal human gait model in the forward dynamics environment. However, a previous study reported that the controllers obtained by the IL method were trained to generate unique actions for any given state although practical scenarios included multiple optimal solutions [8]. Thus, the IL-based controllers had lacks of the ability to flexibly adapt to a wide range of spatial scenarios. Additionally, narrow state spaces focused on reference motions during the IL could lead to the covariate shift problem [8]. The covariate shift problem resulted in divergences when the human gait models received unseen observations or states during the training. As a result, the conventional IL method had poor robustness and recovery performances to external disturbances.

To overcome these limitations of conventional IL methods, noise injection methods have been introduced [8]. The noise injection methods could increase the flexibility and robustness of control policies of robot systems [8]. Therefore, the application of the noise injection method during training controllers of human gait models could increase the balance recovery performance and decrease falls against external disturbances. The objectives of this study were to train the IL-based gait controllers with or without the noise injection method and to analyze the effect of noise injection on the balance recovery performance from external forces. A three-dimensional full-body skeletal human model was developed to implement the gait simulation using IL-based gait controllers. The IL-based gait controllers were prepared with and without the noise injection method. In the case of noise injections, the Gaussian noises were applied to the observation vector to increase the robustness of the controller.

II. METHODS

A. Three-dimensional full-body human gait model

A three-dimensional full-body human gait model was developed in the MuJoCo dynamics environment. Skeletal geometries including segment dynamics information such as masses, inertias, and center of mass's positions were obtained from a previously published full-body model in OpenSim [9]. A mechanical joint configuration of the full-body human gait model was modified from the original OpenSim model [9]. A total of 34 degree-of-freedom was used in the human gait model including spherical, revolute, and universal joints. The neck, shoulder, back, and hip were modeled as spherical joints. The elbow, knee, and metatarsal phalanges were modeled as revolute joints. The ankle was modeled as a universal joint with plantarflexion-dorsi flexion and varus-valgus rotations. The ground-foot contacts were implemented in three spheres on each plantar surface (Fig. 1). The human gait model was actuated by ideal torque actuators in the directions of each joint's degree-of-freedom.

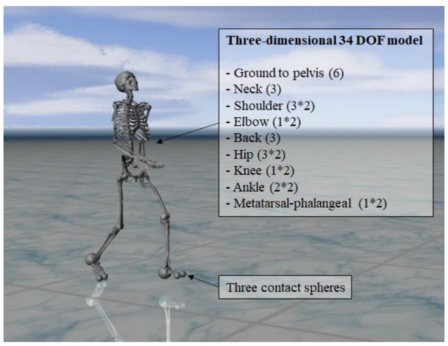

Fig. 1. A three-dimensional human gait model of 34 degree-of-freedom

B. Imitation learning method with deep reinforcement learning for training a gait controller

An initial gait controller without noise injections of the human gait model was trained using an IL method (Fig. 2). The gait controller was designed using a fully-connected artificial neural network with two hidden layers of 512 by 256. A state vector as an input of the gait controller consisted of pelvis orientation, pelvis height, generalized coordinates, and generalized velocities. Then, it generated ideal torques of all joints from the state input vector.

An openly published gait data from CMU Graphics Lab Motion Capture Database was used to prepare reference gait kinematics. The reference gait kinematics was made by modifying the degree-of-freedom of the gait data to match that of the human gait model. A reward value of how well the human gait model tracked the reference gait kinematics was estimated according to a reference study [10]. Specifically, the reward value was calculated by comparing four terms of generalized coordinates, generalized velocities, positions of the hands and feet, and positions of the body's center of mass between the human gait model and reference gait kinematics.

The policy proximal optimization algorithm was used to update the neural network parameters of the gait controller during the IL method with DRL. A total of 16k samples, which were obtained from 200 environments and 800 simulation time steps, were used to update the gait controller at once. After 25k updates, the initial gait controller without noise injections was obtained. The initial gait controller was trained to generate an action vector of joint torques for a given state vector in order to track the reference gait kinematics.

C. Fine-tuning of a gait controller with a noise injection method

The initial gait controller without noise injection was fine-tuned to obtain a robust gait controller by applying noise injections during IL. The noise was added in the state vector with no changes in IL setting such as a reward function and the number of samples for each update. The state vector included generalized coordinates in meters and radians, and generalized velocities in meters per second and radians per second. The noise was determined by the Gaussian distribution. The mean of the noise was set by zero and the standard deviation was dependent on units of state values. The standard deviations concerning translations, rotations, translational velocities, and rotational velocities were set by 0.1 m, 0.35 rad, 1.0 m/s, and 3.5 rad/s, respectively. The fine-tuning was conducted for 10k updates.

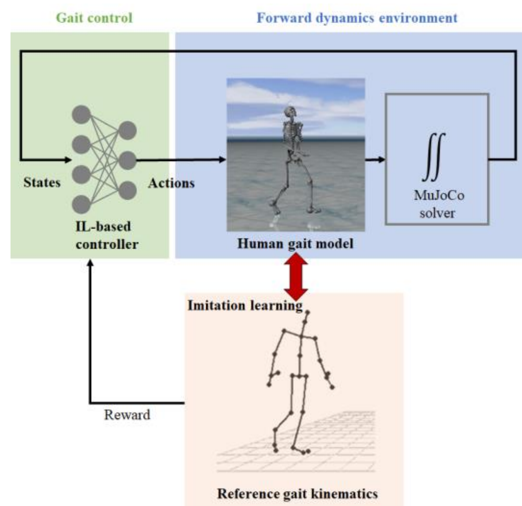

Fig. 2. Imitation learning for training a human gait model in the forward dynamics environment

D. Gait simulation to quantify the effect of noise injections on the robustness of the gait controller

The robustness of the gait controller with and without noise injections was tested through 1,000 repeated gait simulations. The robustness tests were conducted for three different forces of 500 N, 1,000 N, and 1,500 N and three different directions of front, side, and rear. A total of 9,000 simulations were performed for 9 combinations of three forces and three directions. During the gait simulations, the external force was applied to the pelvis for 0.05 seconds after 2 seconds from the simulation start. The number of simulations without falling for 10 seconds was counted to quantify the robustness of the gait controllers.

III. RESULTS

The number of simulations without falling against external forces increased when the gait controller was trained with the noise injection method (TABLE 1). For all forces and directions, the gait controller with noise injections had higher survivals than the gait controller without noise injections. The gait controller without noise injections survived hardly during the 1,000 repeated simulations. Only 6, 27, and 3 simulations survived for forward, lateral, and backward forces of 500 N, respectively. Whereas, the gait controller with noise injections did not experience falling under the same force condition.

In the case of the gait controller with noise injections, the number of survivals without falling was the largest in the forward force, followed by the side force. Although about 90 % of the gait simulations survived under the forward force of 1,000 N, about 60% of the gait simulations survived under the backward force of 1,000 N. Additionally, about 50 % and 10 % of the simulations survived for forward and backward forces of 1,500 N, respectively.

TABLE I. NUMBER OF SURVIVALS WITHOUT FALLING AGAINST EXTERNAL FORCES DURING 1,000 REPEATED GAIT SIMULATIONS

		w/o noise injections	w/ noise injections
Forward direction force	500 N	6	1,000
	1,000 N	2	891
	1,500 N	0	505
Side direction force	500 N	27	1,000
	1,000 N	20	739
	1,500 N	22	392
Backward direction force	500 N	3	1,000
	1,000 N	1	622
	1,500 N	0	134

IV. DISCUSSION

In this study, we quantified the effect of the noise injection method on the robustness of a gait controller against external forces. The noise injections could improve the fall prevention performance when the external forces in the directions of front, side, and rear were applied to the pelvis during walking. In other words, the gait controller with noise injections decreased the number of falls against the external forces, although the gait controller trained by conventional IL without noise injections mostly experienced falls due to the side forces (Fig. 3).

When the gait controllers were trained, the noise injection methods could expand the diversities of state spaces from the optimal unique solution during IL [8]. Thus, the gait controllers experienced state spaces that had the possibility to diverge and fall during the control of the human gait model. These state space samples during IL made the gait controller train to recover stabilities from the state spaces with the potential to diverge and fall. Thus, the noise injection method could improve the robustness of the gait controller against external disturbances such as external forces and partially compensate for the covariate shift problem of IL [8].

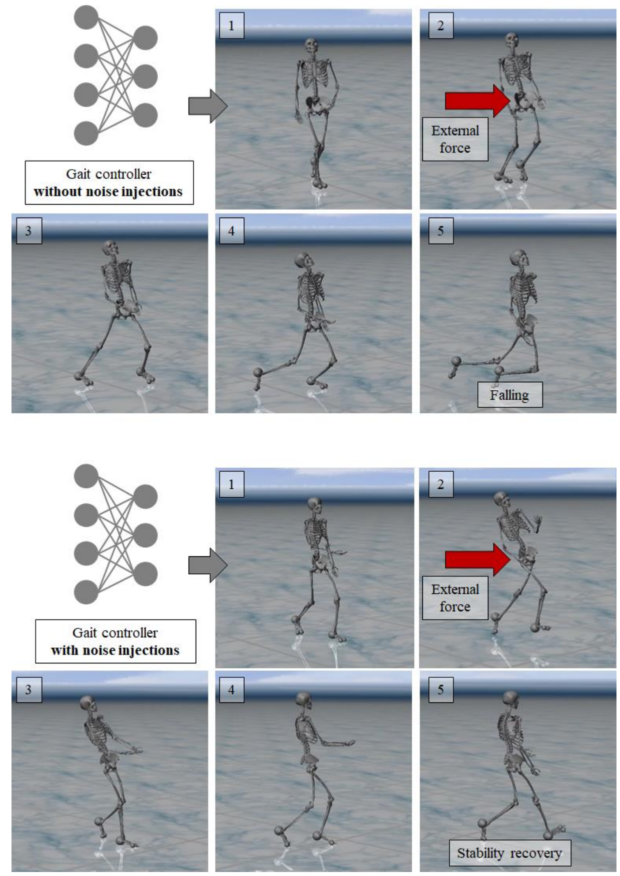

Fig. 3. The robustness of the gait controllers with and without noise injections against external forces

Gait instabilities such as falling are associated with the horizontal velocity of the center of mass and foot placement positions [11]. Especially, medial-lateral perturbations such as side forces and very slow gait speed could affect the center of mass's trajectories and induce gait instabilities [12]. In the case of humans, the decrease in gait stabilities could be compensated by wide step and upper body dynamics [11, 12]. However, the IL-based gait controller could not be trained including these stability compensation strategies. Thus, the conventional IL-based gait controllers had a lack of stability against side and backward direction forces. However, the gait controller with noise injections could retain some stabilities against the side and backward forces. In conclusion, the noise injection method during IL for the human gait model helps improve the robustness and stability of the IL-based gait controller.

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REFERENCES

[1] S. Aoi, N. Ogihara, T. Funato, Y. Sugimoto, and K. Tsuchiya, "Evaluating functional roles of phase resetting in generation of adaptive human bipedal walking with a physiologically based model of the spinal pattern generator," Biol. Cybern. vol. 102, pp. 373–387, March 2010.

[2] Y.-J. Koo, J. K. Seon, G. Lee, and S. Koo, "Influences of Partial Anterior Cruciate Ligament Injury on Anterior Cruciate Ligament Tensional Force and Kinematic Stability During Walking," J. Biomech. Eng. vol. 145, August 2022.

[3] M. Khamar, M. Edrisi, and M. Zahiri, "Human-exoskeleton control simulation, kinetic and kinematic modeling and parameters extraction," MethodsX vol. 6, pp. 1838–1846, 2019.

[4] S. Song and H. Geyer, "A neural circuitry that emphasizes spinal feedback generates diverse behaviours of human locomotion," Physiol. J. vol. 593, pp. 3493–3511, June 2015.

[5] K. G. Pearson, "Generating the walking gait: role of sensory feedback," Prog. Brain Res. pp. 123–129, 2004.

[6] K. Arulkumaran, M. P. Deisenroth, M. Brundage, and A. A. Bharath, "Deep Reinforcement Learning: A Brief Survey," IEEE Signal Process. Mag. vol. 34, pp. 26–38, November 2017.

[7] X. B. Peng, P. Abbeel, S. Levine, and M. van de Panne, "DeepMimic," TOG vol. 37, pp. 1–14, July 2018.

[8] H. Oh, H. Sasaki, B. Michael, and T. Matsubara, "Bayesian Disturbance Injection: Robust imitation learning of flexible policies for robot manipulation," Neural Netw. vol. 158, pp. 42–58, January 2023.

[9] A. Rajagopal, C. L. Dembia, M. S. DeMers, D. D. Delp, J. L. Hicks, and S. L. Delp, "Full-Body Musculoskeletal Model for Muscle-Driven Simulation of Human Gait," IEEE. Trans. Biomed. Eng. vol. 63, pp. 2068–2079, October 2016.

[10] M. Jung and S. Koo, "Physical factors that differentiate body kinematics between treadmill and overground walking," Front. bioeng. biotechnol vol. 10, August 2022.

[11] A. N. Best and A. R. Wu, "Upper body and ankle strategies compensate for reduced lateral stability at very slow walking speeds," Proc. R. Soc. B: Biol. Sci. vol. 287, The Royal Society, p. 20201685, October 2020.

[12] M. Vlutters, E. H. F. Van Asseldonk, and H. Van der Kooij, "Center of mass velocity based predictions in balance recovery following pelvis perturbations during human walking," J. Exp. Biol. January 2016.