Multiscale and Multidisciplinary Modeling, Experiments and Design (2024) 7:2979–2986
https://doi.org/10.1007/s41939-024-00381-y

ORIGINAL ARTICLE

Robotic realization of human perceptual changes with lateral balance task

Kazuya Tomabechi[1] · Ryosuke Morita[2] · Satoshi Ito[2]

Received: 11 October 2023 / Accepted: 22 January 2024 / Published online: 7 March 2024

Abstract

Human motor learning affects not only motion pattern but also perception. On the basis of this idea, we investigated some human-balancing tasks to observe changes in the balance perception. We simulated one of the results to replay the human behavior. In this study, we aim to demonstrate the human adaptive behavior in a motor and sensory system using a robot in a real-world scenario. The subjective upright, i.e., the inclination angle was considered as upright, was evaluated as perception in a balance position, and its lateral shift was determined after a motor-learning task under lateral disturbances. The adaptation dynamics were defined based on our hypothesis that stated that the subjective upright tends to vary toward the posture in which balance can be best maintained. Consequently, the change in the subjective upright similar to the human result was reproduced using a two-link robot that was subjected to the same environmental condition as that in the human experiment.

Keywords Lateral balance · Perceptual adaptation · Motor learning · Robotic validation

1 Introduction

In motor behavior, learning enriches the different motions related to performance such as accuracy, efficiency, and quickness. This learning ability creates several types of behavior under a new environment and consequently increases the space or opportunities to work.

The mechanism of a human motion control is widely studied in terms of the arm-reaching movement (Kawato 1996) according to a powerful learning paradigm, i.e., force field learning (Shadmehr and Mussa-Ivaldi 1994). Although learning often focuses on the motion patterns, which is an output of a motion controller, it has been gotten potential that the sensory system, i.e., the feedback input to the motion controller might be simultaneously adapted. D. J. Ostry reported that the perceptual boundary of a hand somatosensory perception that separates the right and left positions in front of the body shifted to the direction opposite of the force during force field learning of the arm-reaching movements (Ostry et al. 2010). This study illustrates that learning a motor system affects the understanding of sensory signals. However, few studies have considered the perceptual adaptation that accompanies motor learning.

Such sensory adaptation may happen other than the somatosensory perception in the arm-reaching movements. According to this idea, the present study targets human static balance movements. The control of human upright standing involves well-established strategies, namely the ankle strategy and hip strategy, which are recognized as typical methods for maintaining static balance (Horak and Nashner 1986). Recent research determined the effectiveness of these strategies, either individually or in combination, by employing the double pendulum model with intermittent control, passive stiffness, and sensory delay, including an aspect to reproduce the sway in human upright standing effectively. The findings suggest that the ankle strategy emerges as a more robust and efficient approach, while the mixed strategy does not confer advantageous results (Morasso 2022). The ankle strategy utilizes ankle joint torque, particularly effective for ensuring a sufficiently wide base of support and implementing the

✉ Satoshi Ito
ito.satoshi.s0@f.gifu-u.ac.jp

Kazuya Tomabechi
tomabechi@ynl.t.u-tokyo.ac.jp

Ryosuke Morita
morita.ryosuke.w4@f.gifu-u.ac.jp

1 The Graduate School of Information Science and Technology, The University of Tokyo, 7-3-1 Bunkyo, Tokyo 113-8656, Japan

2 Faculty of Engineering, Gifu University, 1-1 Yanagido, Gifu 501-1193, Japan

Center of Pressure (CoP) stabilization strategy. Conversely, the Center of Mass (CoM) stabilization strategy, designed to compensate for balance in situations with a minimal (null) base of support, relies on CoM shift, resembling the lateral balance required on a tightrope. Within this framework, the CoM stabilization strategy aims to maintain the CoM position as close as possible to the vertical line centered on the CoP (Morasso 2020). In robotics, on the other hand, static upright is also studied as a balancing problem. Chiang and Wang (2020) adjusted the robot posture based on the fuzzy logic to adapt the tilt of the slope detected by the inertial gyroscope and accelerometer. Mummolo et al. (2018) evaluated the balance stabilities based on the contact configuration, i.e., single or double support, as well as the COM states. To cope with the environmental disturbance, Liu et al. (2021) achieved the push recovery using force sensors, a gyroscope and an accelerometer in a robotic system. These works, however, treats only the behavioral aspect as motor control output: they did not focus on the adaptation of the sensory input to the control system. With regard to human balance perceptions, the subjective visual vertical (Kheradmand and Winnick 2017) is investigated as a new test on equilibrium disorder. Although the medical tests are required to assess the degree of disorders or the recovery from them, the evaluation of the healthy person should be as important to understand how humans normally behave to the environmental variations.

We have already investigated human balancing behavior from the aspect of the perceptual adaptation, where the subjective upright is treated as the changing perception. Our findings revealed that the subjective upright shifts close to the assumed posture to maintain the balance under a disturbed condition (Kumagai et al. 2015). Furthermore, we described this perceptual change as a dynamic system and reproduced it using computer simulation (Ito et al. 2021). The present study attempts to achieve the changes in the subjective upright shown in Ito et al. (2021) as a robotic behavior: this study is different from the above recent studies in considering the perceptual aspect, and aims at indicating that its control scheme is one of the possible mechanisms in human motion control possessing the learning and perceptual adaptation by demonstrating a human-like behavior with robots.

This paper is organized as follows. Section 2 summarizes the human adaptive behavior observed in our previous experiments. Here, the changes in the subjective upright posture that we aim to reproduce are declared, and our hypothesis on the perceptual adaptation is manifested. Section 3 describes the robot requirements to replay human motion and defines its control method. Section 4 presents the experiments that we conducted using our manufactured robot and discusses the results. Section 5 concludes this paper. The details of our human experiments are presented in the Appendix.

2 Target human behavior

2.1 Perceptual adaptation in balancing motion

Our human experiments revealed that the balancing perception evaluated as a subjective upright in the sitting position could be affected during balancing tasks (Kumagai et al. 2015). The subjective upright here is the lateral deviation of the upper body at which the participants of the experiment felt they were inclining to neither left nor right; it does not mean the physically upright. The details of the experiments are described in Appendix.

The subjective upright was tested three times before and after two motor-learning tasks, namely, motor-learning "0" for the control experiment without disturbance and motor-learning "1" for the experiment with left or right disturbances (see the next section). Figure 1 depicts the result of three tests in (a) the left and (b) the right disturbance conditions respectively, where the vertical axis denotes the rightward deviations of the subjective upright from the average of the first two tests. Six participants' are plotted together in each graph, and the bold line denotes the change of their average with its standard error; the squares or the triangles are plotted

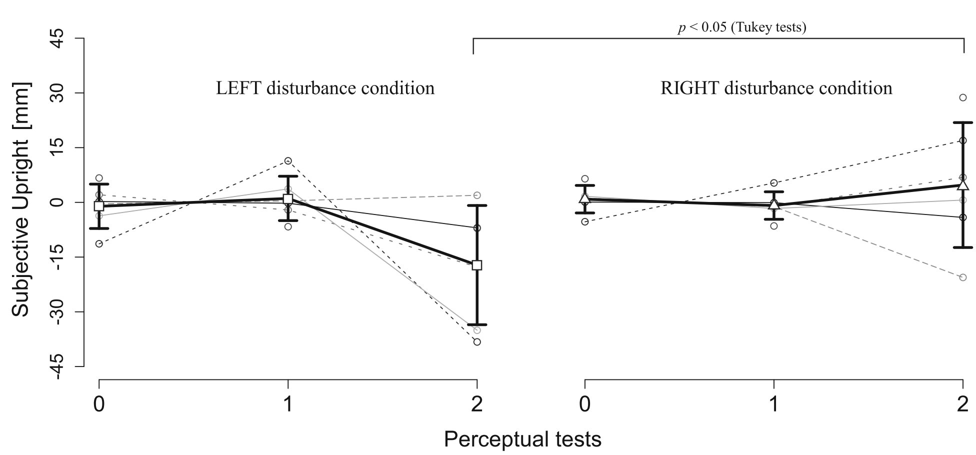


Fig. 1 Experimental results of the perceptual adaptation in human balance

at the average values. The analysis of variance (ANOVA) detected the significant difference among these six averages, while Tukey test reveal the significant difference between two perceptual test “2” ($p < 0.05$).

The object of the robot experiments in this paper is to reproduce the change of the squares/triangles; Motor-learning “0” does not change the subjective upright while Motor-learning “1” shifts it to the same direction of the disturbance.

2.2 Motor learning

The motor learning task was performed on the computer-controlled stool that wholly slides in the lateral direction as well as whose seat rolls independently, as shown in Fig. 2. Motor-learning “0”provided only the lateral slide by fixing its rolling motion. In addition to the lateral slide, Motor-learning “1” contained the rolling disturbance depending on the position of the “virtual rotation axis”: Actually, the stool rotates around the mechanical axis below the mid-line of the seat surface. However, by driving the electric motor for this axis, the rotational direction is controlled depending on the spatial relation between the CoP (Center of Pressure) and this virtual rotation axis. Like a seesaw, the rotation normally occurs in the CoP direction against the mechanical rotation axis. In Motor-learning “1”, however, the rotational direction is decided as the CoP direction against the virtual rotation axis.

In Motor-learning “1” of the left disturbance condition, the virtual rotation axis was shifted to the left and back to the initial position during the one learning trial. To maintain balance with avoiding the seat rotation, the participants need to learn the upper body inclining motion so that their CoP follows the movement of the virtual rotation axis. As a result, they tended to lean the upper body totally to the left side during one trial within Motor-learning “1” of the left disturbance condition.

In the actual experiments, the virtual rotation axis shifted from 0.005 m from the right to 0.02 m to the left of the seat surface in 4 s and turned back in 4 s for the left disturbance condition. The length of the lateral slide was 0.2 m that started towards the left. The opposite process occurred under the right conditions. One trial of the motor-learning experiments took 8 s. Both conditions were applied for one hundred trials each.

2.3 Hypothesis

The actual experiments revealed that two types of upper body posture were observed, as shown in Fig. 3. Among them, the participants that assumed the posture shown in Fig. 3a tended to obtain a left shift of the subjective upright after the motor learning of the left disturbance condition. Our previous study limited our consideration to only the case shown in Fig. 3a (Ito et al. 2021) and the same in this study.

To maintain the balance under a no-disturbance situation, we normally attempt to have the upright, in other words, vertical posture. This posture is the best-balanced one where the gravity does not generate any moment around the base and thus no base-joint torque theoretically required at this posture. Considering the fact that the best-balanced posture is usually upright since there are no disturbance in our normal situation, we hypothesized that the participants tend to regard the best-balanced posture as upright even in a disturbed situation. In Motor-learning “1” of the left disturbance condition, the best-balanced situation is the one that achieves the task requirements: the upper body tends to lean leftward to follow the virtual rotation axis shifting to the left and back. Accordingly, we predict that the subjective upright changes to the left as the result of the motor learning.

In short, we can explain the result in Fig. 1 based on the hypothesis that the subjective upright is affected in terms of this best-balanced posture and changes so as to approach it.

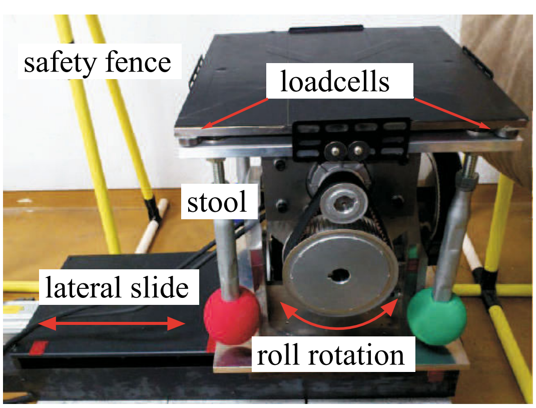


Fig. 2 Stool with lateral slide and rolling movements

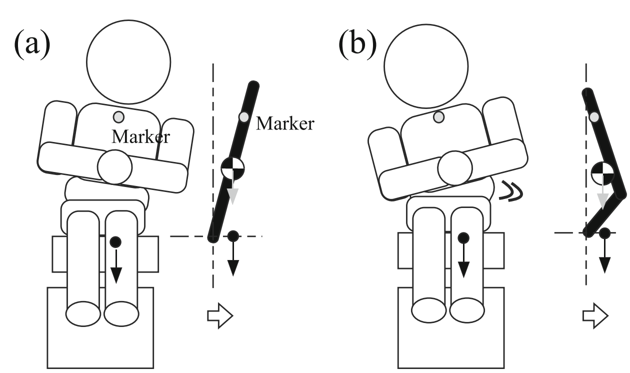


Fig. 3 Two postures observed for the left disturbance

2.4 Control strategy

To mathematically describe our hypothesis, we modeled the upper body of a participant on a stool as a two-link structure with a base link located within the frontal plane according to the two observed postures shown in Fig. 3.

With respect to this link model, the following control strategy was introduced. The torque in the upper joint maintained a straight posture, as shown in Fig. 3a, whereas that in the base joint controlled the CoP position to follow the virtual rotation axis. This control made the upper body incline to the same side as the disturbance, which was the side where the virtual rotation axis deviated. During this balancing motion, the best balanced posture appeared as the result of the control strategy. Finally, the subjective upright was adjusted in order to approach the best-balanced posture.

3 Robot design and its control

3.1 Requirements

The objective of this study is to reproduce the human perceptual adaptation (Fig. 1) as robotic behavior based on the hypothesis and control strategy presented in Sect. 2. A simple robot was preferred to focus on the essence of adaptation. From this perspective, we designed and manufactured this robot.

Some of the necessary specifications are summarized and listed in Table 1.

- All necessary motions are within the frontal plane.
- The robot consists of two joints, two links, and a base.
- It can detect joint-angle deviation and its CoP position.
- Its size and weight is suitable to be easily and safely handled for the experiments on the stool.

Table 1 Robot specifications

Weight	About 1.6 (kg)
Length	W 0.15 (m) × D 0.15 (m) × H 0.46 (m)
Material	A2017
Load Cell	LMA-A-50N-P (KYOWA)
Motor	DCX22S GB KL 24V (Maxon Motor)
Motor Gear	GPX22HP 44:1 (Maxon Motor)
Encoder	ENX16 EASY 1024IMP (Maxon Motor)

3.2 Mechanical structure

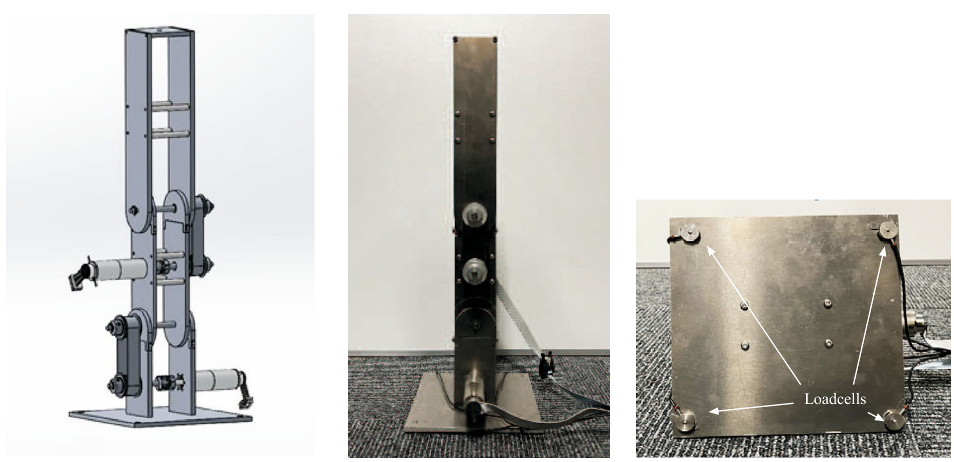
The designed robot, which was drawn using computer-aided design, is shown in Fig. 4a. Its specifications are listed in Table 1. Figure 4b is a photo of the manufactured robot.

The size was designed to be quite smaller than a human being considering its safety in the event of tumbling. The base joint was located at the center of a 0.15-m-square base link. Four load cells were attached to each corner of this base, as shown in Fig. 4c, where the distance from the center was the same in all load cells. The upper joint axis was parallel to the base-joint axis. The joint and motor axes were connected by a timing belt that was wound around the pulleys of the same radius attached to each axis. The sliding structure adjusted the distances between the pulleys to provide sufficient tension to the timing belt.

3.3 Control

The deviation in base-joint angle θ_1 and upper joint angle θ_2 could be obtained from the rotary encoder installed in each motor. Another sensory information from the load cells

Fig. 4 Designed and manufactured robot



(a) Drawing (b) Photo (c) Loadcells

provided X_{cop}, the CoP position from the base center.

$$X_{\mathrm{cop}} = \frac{F_{\mathrm{FR}} + F_{\mathrm{RR}} - F_{\mathrm{FL}} - F_{\mathrm{RL}}}{F_{\mathrm{FR}} + F_{\mathrm{RR}} + F_{\mathrm{FL}} + F_{\mathrm{RL}}} \cdot \ell_w \quad (1)$$

where F_* denotes the vertical force of the ground reaction detected by the load cells and it subscribes their positions. FR, RR, FL, and RL represent the front right, rear right, front left, and rear left, respectively. ℓ_W represents the lateral distance between the center axis of the base and the load cells: $\ell_W = 0.075$ m in the robot.

To achieve the control strategy presented in Sect. 2.4, torque in the upper joint τ_2 was defined as the position control in the joint space, i.e.,

$$\tau_2 = -D_2\dot{\theta}_2 + K_2(\theta_{d2} - \theta_2), \quad (2)$$

whereas base joint torque τ_1 was defined to let CoP follow the position of virtual rotation axis X_{vr} (Ito et al. 2021):

$$\tau_1 = -D_1\dot{\theta}_1 + K_1(\theta_{d1} - \theta_1) + K_{\mathrm{cop}} \int (X_{\mathrm{vr}} - X_{\mathrm{cop}})\mathrm{d}t. \quad (3)$$

Here, $\dot{}$ denotes the time derivative, D_1 and D_2 are the derivative gains, K_1 and K_2 are the proportional gains, θ_{d1} and θ_{d2} are the desired portion of θ_1 and θ_2, respectively, that should be zero for the straight upright posture on a horizontal plane, and K_{cop} is the feedback gain of the CoP position control. X_{vr} is assumed known because the position of virtual rotation axis is visually provided in the human experiments.

When a disturbance is applied, particularly as a constant external force, the control law (3) achieves a stationary posture where CoP position settles at its desired value, independent of θ_{d1}. Even if θ_{d1} is set to the upright direction, the constant external force and gravity are canceled in their moment around the base joint at the stationary state. This implies that the base joint does not have to generate any torque, because the moment around the base joint is already zero (no disturbance) due to the cancellation. Such a posture is advantageous from an energetic point of view. We will refer to this posture as Θ_d later in this section.

Here, we introduced a new variable ϕ that represented the subjective upright, which was assumed as a base-joint angle that the robot considered upright in this position. In our scenario, the best-balanced posture was considered as upright. The control law, i.e., Eq. (3), achieved the best posture where the moment from the external force and the gravity were balanced to zero around the base joint, i.e., zero base-joint torque to maintain this posture, and CoP was located at the center of the base link when the external disturbance was constant (Ito et al. 2001). Because Eq. (3) can be written as the PD control with the desired posture Θ_d

$$\tau_1 = -D_1\dot{\theta}_1 + K_1(\Theta_d - \theta_1), \quad (4)$$

where

$$\Theta_d = \theta_{d1} + K_{\mathrm{cop}} \int (X_{\mathrm{vr}} - X_{\mathrm{cop}})\mathrm{d}t / K_1. \quad (5)$$

Θ_d is regarded as the best-balanced posture in this context.

Subsequently, we defined the perceptual adaptation dynamics so that the subjective upright approached the best posture Θ_d. In our case, the disturbances were periodic; thus, Θ_d became oscillative. This is the reason why a low-pass filter (LPF) was applied to extract the desired posture by averaging.

$$\dot{\phi} = K_\phi(\mathrm{LPF}(\Theta_d) - \phi) \quad (6)$$

where K_ϕ is the inverse of the time constant of the adaptation dynamics.

4 Experiments

4.1 Setup

Two independent controllers control the robot and stool motion. A PC that operates on Interface Linux System 7 (Interface Corporation) controls the robot at 1-ms period. This PC contains three extended processing boards. The pulse-counter board (PCI-6205C, Interface Corporation) receives the pulse signals from the optical rotary encoder of the motors to obtain the deviation in the robot-joint angles. The analog-to-digital converter board (PEX-340416, Interface Corporation) receives the force signal from the load cells through the signal conditioner (MCA-8A, Kyowa Electronic Instruments Co., Ltd.). The CoP position is estimated using these signals. According to the robot-joint angles and the CoP information, each joint torque of the robot is computed by the PC. The result is output from the digital-to-analog converter board (PCI-H3133, Interface Corporation) as voltage signals, which are amplified by the motor driver (SmartDriveDuo-10, Cytron Technologies) and drive the joint motors. Figure 4b shows a photograph of the robot in the experiments.

The same stool that we introduced for the human experiments is used in the robot experiments.

4.2 Experimental condition

During the experiments, the stool is made laterally slide in a sinusoidal manner: the PD control is applied to follow the sine wave whose amplitude is 0.4m and period is 8 s. In addition, the roll rotation of the stool seat is achieved as a position control whose desired position varies depending on the current CoP as well as the virtual rotation axis. Let θ_0 the roll rotation angle of the stool. Then the roll rotation torque τ_0 is defined as

$$\tau_0 = -D_0\dot{\theta}_0 + K_0(\theta_{d0} - \theta_0), \tag{7}$$

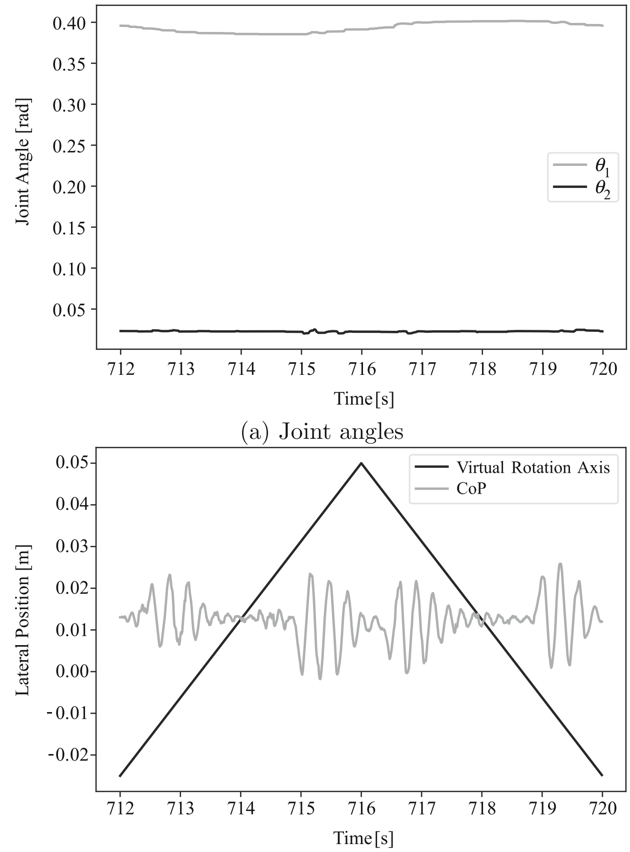
$$\theta_{d0} = K_{\mathrm{roll}}(X_{\mathrm{cop}} - X_{\mathrm{vr}}), \tag{8}$$

where θ_{d0} is the desired angle of the roll rotation of the stool, D_0 and K_0 are the derivative and proportional gains, respectively. K_{roll} is a gain that adjusts the relation between the CoP position from the virtual rotation axis and θ_{d0}. Namely, if the CoP position is larger (more to the right) than the virtual rotation axis, the desired roll angle increases (turns right). The virtual rotation axis is made to move left and right at constant speed v_{c},

$$X_{\mathrm{vr}} = \rho(v_{\mathrm{c}}|t - t_{\mathrm{m}}| - x_0) \tag{9}$$

where t is the time for a one motor-learning trial, t_{m} is the half duration of the one trial, ρ indicates a left ($\rho = +1$) or right ($\rho = -1$) disturbance condition, and x_0 is the motion offset. This roll rotation is fixed in Motor-learning “0”.

Actual value of the parameters in the experiments are: $D_0 = 1$, $D_1 = 0.0002$, $D_2 = 0.0004$, $K_0 = 3000$, $K_1 = 0.25$, $K_2 = 0.16$, $K_{\mathrm{cop}} = 0.06$, $K_\phi = 0.008$, $K_{\mathrm{roll}} = 1$, $\theta_{d1} = 0$ rad, $\theta_{d2} = 0$ rad, $v_{\mathrm{c}} = 0.01875$ (= 0.075/4) m/s, $x_0 = 0.05$ m and $t_{\mathrm{m}} = 4$ s. The first-order LPF with a time constant of 1 s is applied in Eq. (6).



(a) Joint angles

(b) CoP

Fig. 5 Experimental results under the right-disturbance condition

4.3 Results

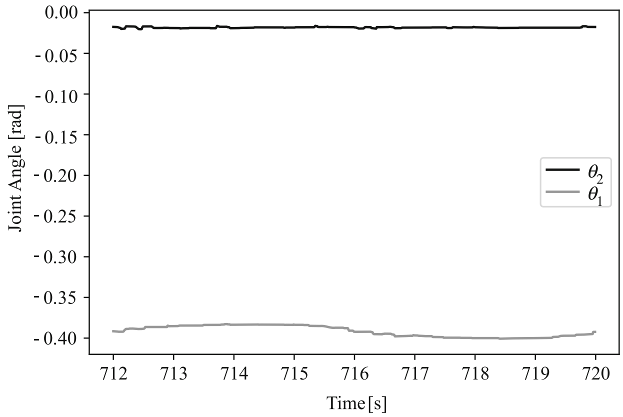
The results for the right- and left-disturbance conditions are shown in Figs. 5 and 6, respectively. Both figures show the time course of each joint angle in (a) and CoP deviation from the base center in (b) at the 90th trial from 712 to 720 s until which the robot motion is expected to reach stationary. Figure 7 shows the changes in subjective upright ϕ under (a) left- and (b) right-disturbance condition from 0 to 800 s. Note that the same result under the control condition is depicted within their graph from -800 to 0 s.

4.4 Discussion

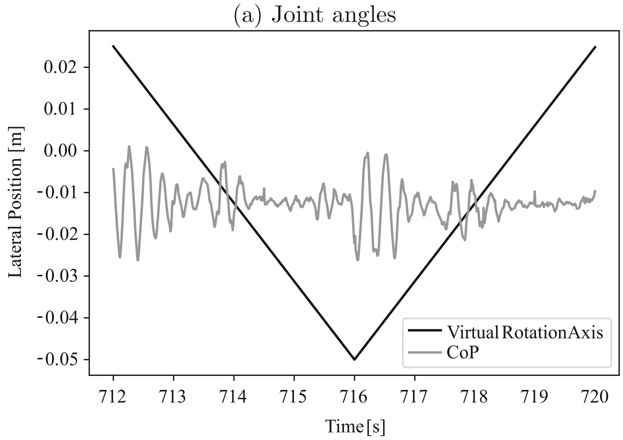
At the 90th trials, the upper joint was controlled at approximately 0°, as shown in Figs. 5a and 6a, which show that the straight upper body was maintained in both conditions. Due to the high positional gain $K_1 = 0.25$ with respect to the CoP feedback gain $K_{\mathrm{CoP}} = 0.06$ to secure the robot stability during the experiment, the base joint displacement was also slight (about 0.02 rad), resulting that the CoP did not vary except the mechanical vibration of the whole robot (Figs. 5b and 6b). Consequently, the CoP did not follow the desired triangular trajectory, but the CoP feedback brought the CoP to the average position of the desired trajectory, rightward (positive) in the right disturbance condition whereas leftward (negative) in the left disturbance condition. Actually, this behavior was achieved by inclining the whole upper body; base joint angle θ_1 stayed at approximately ± 0.4 rad. According to our hypothesis, the subjective upright approaches this best-balanced posture $\Theta_d \simeq \pm 0.4$rad. Such changes are well represented in Fig. 7: the subjective upright ϕ approaches $+0.4$ rad in the right condition and -0.4 rad in the left condition. They are similar to the human results in Fig. 1 (changes of squares and triangles) considering that one hundred trials in the control condition (Motor-learning “0”) existed between perceptual test 0 and 1 as well as one hundred trials in the disturbed condition (Motor-learning “1”) between perceptual test 1 and 2. It indicates that the human adaptive behavior in this balancing task was reproduced as robot behavior.

5 Conclusion

This study has demonstrated the adaptive behavior in balance perception that accompanies balance motor learning as a robotic motion in the real world. The subjective upright was being focused as a parameter in the balance perception, and it was updated based on the hypothesis that the subjective



(a) Joint angles



(b) CoP

Fig. 6 Experimental results under the left-disturbance condition

upright approaches the best posture so that zero base-joint torque is required to maintain balance with canceling the moment between the gravity and the external disturbance when the disturbance is constant. By defining the adaptation dynamics, similar changes in the subjective upright is reproduced. Replay of the human behavior confirms that our proposed control scheme can be one of the candidates for human motor mechanisms. To make the human model more sophisticated, we need to employ some skillful and elaborate human actions from the motion measurement as our future works.

Author Contributions Kazuya Tomabechi conducted the experiments and summarized its results. Ryosuke Morita contributed to establish the control method and joined the construction of the experimental setup. Satoshi Ito organized this study, proposed the main idea, constructed the control concept and wrote the manuscript.

Funding Open Access funding provided by Gifu University. A part of this study was supported by Grant-in-Aid for Scientific Research(B) (No. 16H02879) of Japan Society for the Promotion of Science.

Data Availability Data sets generated during the current study are available from the corresponding author on reasonable request.

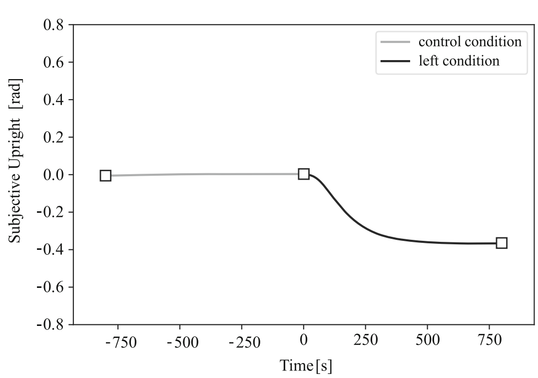
Declarations

Conflict of interest The authors declare that they have no conflict of interest.

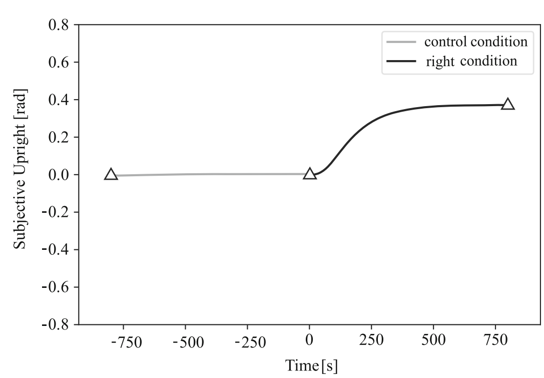
Consent for publication All authors consent to publish their work in this journal.

Appendix: Human-balance experiments

Our experimental setup for human motor learning and balance perception is illustrated in Fig. 8.



(a) Left-disturbance condition.



(b) Right-disturbance condition.

Fig. 7 Adaptive changes of subjective upright posture

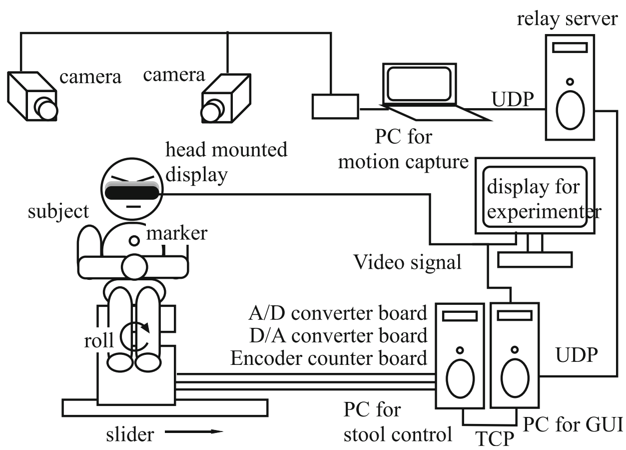


Fig. 8 Setup for human experiments

In the motor-learning phase for human balance, two disturbance conditions were provided using a specially made stool. The seat of this stool could be rotated by a motor around the roll axis 0.2 m below it. Further, it could make itself slide in the lateral direction.

Although the lateral slide was the same under both conditions, the conditions were differentiated by the roll disturbance. To create a roll disturbance using feedback control, we introduced the "virtual rotation axis" explained in Sect. 2.2. In Motor-learning "1", a laterally biased shift in the virtual rotation axis was provided together with the stool slide. However, precedent Motor-learning "0" for the control experiment contained only the slide disturbance by fixing the roll rotation.

Sitting on the stool, the participants wore the head mounted display (HMD) to break the outside visual information as well as to indicate the seat tilt and current position of the virtual rotation axis on its screen with the computer graphics. The participants were asked to maintain their balance with the seat surface being horizontal. Thus, they had to synchronize their upper body movement with the virtual rotation axis so that CoP followed it to avoid roll rotation. They tended to incline to the left under the left condition. This balancing motion was expected to be learned during the motor-learning phase.

Before and after these experiments, the participants took a perceptual test to detect their subjective upright. The perceptual tests were conducted on the same stool as used in the motor-learning phase. On the screen of the HMD, the small bar moving in synchronization with the lateral sway of the upper body was displayed. The participants were instructed to change their lateral position of the upright body to the target posture in which this bar stays at the center of the HMD marked with the thin line in computer graphic. Thus, the initial display position of this bar can control the target posture. At the target posture, the participants had to answer to the question, "which direction do you feel inclined to, left or right". Testing the feeling of the incline at the various target posture by changing the initial position of the bar according to PEST (Taylor and Creelman 1967), the subjective upright was detected.

Six participants were recruited for each of the left and right conditions of motor learning. This experiment was approved by the Ethical Review Committee of the Graduate School of Medical Science in Gifu University (No. 26-55).

The results of the three perceptual tests are shown in Fig. 1, where the vertical axis denotes the lateral deviation of the upper body part. The lines in the graphs are aligned so that the average of the first and second perceptual tests becomes zero.

References

Chiang SY, Wang JL (2020) Posture control for humanoid robot on uneven ground and slopes using inertial sensors. Adv Mech Eng 12(9):1687814020957181

Horak FB, Nashner LM (1986) Central programming of postural movements: adaptation to altered support-surface configurations. J Neurophysiol 55(6):1369–1381

Ito S, Nishigaki T, Kawasaki H (2001) Upright posture stabilization by ground reaction force control. In: Proceeding of the international symposium on measurement, analysis and modeling of human functions, pp 515–520

Ito S, Tomabechi K, Morita R (2021) Perceptual adaptation during a balancing task in the seated posture and its theoretical model. Biol Cybern 115:207–217

Kawato M (1996) Computational theory of brain. Sangyo Tosho **(in Japanese)**

Kheradmand A, Winnick A (2017) Perception of upright: multisensory convergence and the role of temporo-parietal cortex. Front Neurol 8:552

Kumagai S, Ito S, Matsushita K et al (2015) The balance perception changes by motor learning with active trunk movements. In: Proceedings of 2015 IEEE/SICE international symposium on system integration (SII2015), pp 936–941

Liu CC, Lee TT, Xiao SR et al (2021) Bipedal walking with push recovery balance control involves posture correction. Microsyst Technol 27(4):1747–1758

Morasso P (2020) Centre of pressure versus centre of mass stabilization strategies: the tightrope balancing case. R Soc Open Sci 7:200111

Morasso P (2022) Integrating ankle and hip strategies for the stabilization of upright standing: an intermittent control model. Front Comput Neurosci 16:956932

Mummolo C, Peng WZ, Gonzalez C et al (2018) Contact-dependent balance stability of biped robots. J Mech Robot 10(2):021009

Ostry DJ, Darainy M, Mattar AA et al (2010) Somatosensory plasticity and motor learning. J Neurosci 30(15):5384–5393

Shadmehr R, Mussa-Ivaldi FA (1994) Adaptive representation of dynamics during learning of a motor task. J Neurosci 14(5):3208–3224

Taylor MM, Creelman CD (1967) Pest: efficient estimates on probability functions. J Acoust Soc Am 41(4A):782–787