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Interlimb coordination is not strictly controlled during walking

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Takahiro Arai 1,7, Kaiichiro Ota²,7, Tetsuro Funato³, Kazuo Tsuchiya⁴, Toshio Aoyagi⁵ & Shinya Aoi 16 ⊠

In human walking, the left and right legs move alternately, half a stride out of phase with each other. Although various parameters, such as stride frequency and length, vary with walking speed, the antiphase relationship remains unchanged. In contrast, during walking in left-right asymmetric situations, the relative phase shifts from the antiphase condition to compensate for the asymmetry. Interlimb coordination is important for adaptive walking and we expect that interlimb coordination is strictly controlled during walking. However, the control mechanism remains unclear. In the present study, we derived a quantity that models the control of interlimb coordination during walking using two coupled oscillators based on the phase reduction theory and Bayesian inference method. The results were not what we expected. Specifically, we found that the relative phase is not actively controlled until the deviation from the antiphase condition exceeds a certain threshold. In other words, the control of interlimb coordination has a dead zone like that in the case of the steering wheel of an automobile. It is conjectured that such forgoing of control enhances energy efficiency and maneuverability. Our discovery of the dead zone in the control of interlimb coordination provides useful insight for understanding gait control in humans.

During human walking, the left and right legs move alternately, half a stride out of phase with each other¹. In general, various locomotion parameters, such as gait frequency, stride length, and duty factor, change if the gait speed varies. However, the antiphase relationship of the leg motion remains unchanged. This is true even if the gait pattern changes to running. By contrast, during walking in which there is left-right asymmetry with regard to the body or environment, such as walking with unilateral leg loading², walking along a curved path³, or walking on a split-belt treadmill⁴, the relative phase between the legs shifts from the antiphase condition to compensate for the asymmetry. In addition, the phase relationship fluctuates significantly during walking of elderly people and patients with neurological disabilities, such as those caused by stroke or Parkinson's disease⁵⁻⁹. These findings indicate that appropriate relative phase (that is, appropriate interlimb coordination) is important for adaptive walking. This seems to suggest that the relative phase is strictly controlled to remain the appropriate relative phase during walking of healthy young people, with the relative phase quickly returning to the appropriate relative phase after being perturbed away from it.

To understand interlimb coordination during human walking, it has been investigated how the relative phase between the motion of the left and right legs depends on the situations described above. However, it remains largely unclear to what extent it is strictly controlled in each situation. This is mainly because there are limitations on the degree to which the control of interlimb coordination can be quantitatively elucidated due to the complexity of neural dynamics, musculo-skeletal dynamics, and interactions with the environment during walking. Elucidating the control of interlimb coordination would not only clarify the adaptive strategy in human walking, but also contribute to the development of rehabilitation techniques for persons with gait disorders and gait assistive devices, such as robotic exoskeletons¹⁰⁻¹².

The present study aims to quantitatively clarify the control of interlimb coordination during human walking by taking advantage of both data science and dynamical systems theory, employing the Bayesian inference

¹Center for Mathematical Science and Advanced Technology, Japan Agency for Marine-Earth Science and Technology, Yokohama, 236-0001, Japan. ²Cybozu, Inc., 2-7-1 Nihombashi, Chuo-ku, Tokyo, 103-6027, Japan. ³Department of Mechanical Engineering and Intelligent Systems, Graduate School of Informatics and Engineering, The University of Electro-Communications, 1-5-1 Choufugaoka, Choufu, Tokyo, 182-8585, Japan. ⁴Department of Aeronautics and Astronautics, Graduate School of Engineering, Kyoto University, Kyoto daigaku-Katsura, Nishikyo-ku, Kyoto, 615-8540, Japan. ⁵Graduate School of Informatics, Kyoto University, Yoshida-Honmachi, Sakyo-ku, Kyoto, 606-8501, Japan. ⁶Department of Mechanical Science and Bioengineering, Graduate School of Engineering Science, The University of Osaka, 1-3 Machikaneyama, Toyonaka, Osaka, 560-8531, Japan. ⁷These authors contributed equally: Takahiro Arai, Kaiichiro Ota. $\boxed{}$ e-mail: aoi.shinya.es@osaka-u.ac.jp

method^{13,14} and phase reduction theory^{15–20}. Specifically, we model the rhythmic motion of the left and right legs by two coupled limit-cycle oscillators and describe these dynamics using two coupled phase oscillators. The phase coupling function between the two oscillators represents the nature of the control of the relative phase between the motion of the legs, i.e., interlimb coordination. To identify this phase coupling function in human walking, we first measured the leg motion during walking of subjects on a treadmill with intermittent perturbations in the belt speed. Next, from the measured time-series data, we derived the phase coupling function using the Bayesian inference method. We analyze the characteristics of the control of interlimb coordination during human walking on the basis of this function.

Results

Walking experiment

We measured kinematic data through observation of eight healthy men (Subjects A-H) during walking on a treadmill whose belt speed was intermittently disturbed from 1.0 m/s for a short time (Fig. 1a). More precisely, the belt speed was temporarily increased or decreased by 0.6 m/s over a period of 0.1 s, and then returned to 1.0 m/s over a period of 0.1 s. We regard the disturbance of the belt speed from 1.0 m/s as an external perturbation, written by p(t). This perturbation resulted in the sudden collapse of the antiphase relationship of the leg motion and allowed us to investigate how the relative phase of the leg motion recovered after being disturbed. Each trial lasted approximately 60 s and contained ten disturbances during which the speed was varied. These disturbances were separated by intervals of approximately 5 s, which was sufficiently long to allow the return to normal steady-state walking. We used three types of perturbation conditions for each trial: acceleration, deceleration, and mixed conditions. Only temporary acceleration and deceleration perturbations of the belt speed were applied under the acceleration and deceleration conditions, respectively, while both perturbations were applied randomly under the mixed condition. From the measured kinematic data, we calculated the elevation angle of the limb axis, which connects the hip and toe of each leg. The angles are denoted by $\varphi_1(t)$ and $\varphi_{\rm R}(t)$, where the subscripts L and R indicate the left leg and right leg, respectively.

Modeling the control of interlimb coordination using coupled phase oscillators

We model the motion of the left and right legs by two coupled limit-cycle oscillators, whose phases are ϕ_L and $\phi_R \in (0, 2\pi]$, and describe these dynamics using phase equations on the basis of the phase reduction

theory^{15–18} as follows (Fig. 1b):

$$\dot{\phi}_{\rm L}(t) = \omega_{\rm L} + \Gamma_{\rm LR}(\phi_{\rm R} - \phi_{\rm L}) + Z_{\rm L}(\phi_{\rm L})I(t) + \xi_{\rm L}(t), \qquad (1)$$

$$\dot{\phi}_{\mathrm{R}}(t) = \omega_{\mathrm{R}} + \Gamma_{\mathrm{RL}}(\phi_{\mathrm{L}} - \phi_{\mathrm{R}}) + Z_{\mathrm{R}}(\phi_{\mathrm{R}})I(t) + \xi_{\mathrm{R}}(t).$$
(2)

Here, $\omega_{\rm L}$ and $\omega_{\rm R}$ are the natural frequencies, $\varGamma_{\rm LR}$ and $\varGamma_{\rm RL}$ are phase coupling functions, $Z_{\rm L}$ and $Z_{\rm R}$ are phase sensitivity functions, I is an external perturbation (rescaled from p(t)), and $\xi_{\rm L}$ and $\xi_{\rm R}$ are independent Gaussian white noise terms that represent experimental uncertainty, which satisfy $\langle \xi_i(t) \rangle = 0$ and $\langle \xi_i(t) \xi_i(s) \rangle = \sigma_i^2 \delta_{ii} \delta(t-s)$ for (i, j) = (L, R) and (R, L), where σ_i is the intensity of the Gaussian noise ξ_i and δ_{ii} and $\delta(t)$ are the Kronecker and Dirac delta functions, respectively. We determined $\phi_i(t)$ ($i \in (L, R)$) from the measured time series of the kinematic angle $\varphi_i(t)$, and also determined I(t) from the measured time series of the external perturbation p(t). We determined the best values for ω_i , Γ_{ip} and Z_i ((*i*, *j*) = (L, R), (R, L)) from the time series of $\phi_i(t)$ and I(t) using the Bayesian inference method^{14,17,21,22}. We did the same for σ_i in order to determine the extent to which Eqs. (1) and (2) are capable of modeling the dynamics of the observed human walking. We deem that a small intensity indicates that our deterministic model properly describes the dynamics and that the influence of the stochastic process is small. In previous studies^{14,21,22}, $Z_i I$ was not used in the identification of the phase equation, and the parameter values were obtained using data measured after external perturbations were applied. However, including $Z_i I$ in this identification allowed us to determine the parameter values more accurately through use of data measured while external perturbations were being applied.

Using phase equations derived through the procedure described above, we investigate how the relative phase between the motion of the legs, i.e., interlimb coordination, is controlled during human walking. Specifically, if we ignore the phase response to the external perturbation in Eqs. (1) and (2) and focus on the transient dynamics after the perturbation is applied, we obtain the following equation for the relative phase $\Delta_{LR} = \phi_R - \phi_L$:

$$\dot{\Delta}_{LR} = \omega_{R} - \omega_{L} + \Gamma_{RL}(-\Delta_{LR}) - \Gamma_{LR}(\Delta_{LR}) + \xi_{R} - \xi_{L}$$

$$:= f(\Delta_{LR}) + \xi_{LR}.$$
 (3)

Here, we have $\xi_{LR} = \xi_R - \xi_L$, which satisfies $\langle \xi_{LR}(t) \rangle = 0$ and $\langle \xi_{LR}(t) \xi_{LR}(s) \rangle = \sigma_{LR}^2 \delta(t-s)$, where $\sigma_{LR} := \sqrt{\sigma_R^2 + \sigma_L^2}$, and $f(\Delta_{LR})$ describes the deterministic dynamics of Δ_{LR} , i.e., the control of interlimb

a Measurement of the leg motion, represented by $\varphi_i(t)$ ($i \in (L, R)$), during walking on a treadmill with a perturbation in the belt speed, represented by p(t). b Two coupled limit-cycle oscillators with phases $\phi_i(t)$ ($i \in (L, R)$) whose dynamics are described by phase equations with phase coupling functions $\Gamma_{ii}(\phi_i - \phi_i)$, phase sensitivity functions $Z_i(\phi_i)$, external perturbation I(t), and Gaussian noise ξ_i ((i, j) = (L, R), (R, L)). c Integration of the measured data and phase equations to derive the dynamics of the relative phase Δ_{LR} , which reflects the control of interlimb coordination. When $\Delta_{LR} = \pi$, corresponding to B, the legs move in an exactly alternating manner. As Δ_{LR} moves away from π , the deviation from this antiphase relationship increases (see A and C, with $\Delta_{LR} = \Delta^A$ and Δ^C). If the interlimb coordination is strictly controlled to maintain the antiphase relationship, the function $f(\Delta_{IR})$, which describes the control of interlimb coordination, should intersect the horizontal axis at π with a steep negative slope.

Fig. 1 | Schematic diagram of the study.



coordination. If the antiphase relationship, $\Delta_{LR} = \pi$, is tightly maintained, it is required that $f(\Delta_{LR})$ be 0 and have a steep negative slope at $\Delta_{LR} = \pi$ (Fig. 1c).

Figure 2 displays the time series of $\varphi_i(t)$, $\phi_i(t)$, $\Delta_{LR}(t)$, and p(t) $(i \in (L, R))$ for one representative subject (Subject G). There, an increase of $\phi_i(t)$ by 2π represents one cycle of $\varphi_i(t)$. It is seen that $\Delta_{LR}(t)$ is greatly disturbed in response to the external perturbation (highlighted in green) and then returns to the neighborhood of π , the antiphase value. However, it does not converge to π but rather fluctuates about this value. This suggests that the dynamics of the relative phase possesses Lyapunov stability about π , not asymptotic stability. We now proceed to elucidate how $f(\Delta_{LR})$ reflects this stability.

Figure 3a, b display the functions Z_i ($i \in (L, R)$) and $f(\Delta_{LR})$, respectively, evaluated from the data for one representative subject (Subject G). It is seen that both $Z_{\rm L}$ and $Z_{\rm R}$ possess unimodal shapes with peaks near π and are close to zero in the range from 0 to $\pi/2$ for all perturbation conditions. Because $\Delta_{\rm LR}$ fluctuates within a narrow region around π , as shown in Fig. 2, there was not a sufficient amount of data outside this region for the evaluation of $f(\Delta_{LR})$. Therefore, we limited our evaluation of $f(\Delta_{LR})$ to a range of 3 standard deviations around the mean of the observed Δ_{LR} . Although we expected that $f(\Delta_{LR})$ would intersect the horizontal axis at one point near π with a steep negative slope, in accordance with the strict control of interlimb coordination, as shown in Fig. 1c, the results were not what we expected for any of the perturbation conditions. Specifically, we found that although $f(\Delta_{LR})$ has a steep negative slope sufficiently far from π , it is close to zero near π . Thus, we found that $f(\Delta_{LR})$ has a flat region with a value close to 0 in the neighborhood of the antiphase condition. This result indicates that the relative phase between the legs is not actively controlled until the deviation from the antiphase condition exceeds a certain threshold, where the antiphase relationship is lost as shown in Fig. 3c. We obtained similar results from the other subjects (see Supplementary Note 1 and Supplementary Fig. 1). These characteristic properties of $f(\Delta_{LR})$ remained even when we excluded $Z_i I$ from the phase equation in the determination of $f(\Delta_{LR})$ (see Supplementary Note 2 and Supplementary Fig. 2). However, the form of $f(\Delta_{IB})$ obtained with $Z_i I$ exhibits these characteristics more clearly than that without Z_iI .

Evaluating the flat region in the control of interlimb coordination

To clarify the universality of our findings in the control of interlimb coordination represented by $f(\Delta_{LR})$, specifically, the existence of a flat region in which $f(\Delta_{LR})$ is close to 0 in the neighborhood of $\Delta_{LR} = \pi$, and steep negative slopes outside this flat region (Fig. 3c), we compared the results for $f(\Delta_{LR})$ among the subjects. For this purpose, we approximated $f(\Delta_{LR})$ by a piecewise linear function to characterize these properties within 3 standard deviations around the mean of the observed Δ_{LR} , as shown in Fig. 4a. There, l_C is the length of the flat region, which reflects the extent to which the deviation

from the antiphase condition is ignored, and $g_{\rm L}$ and $g_{\rm R}$ are the slopes in the regions to the left and right of the flat region, respectively, which reflect how rapidly the deviation outside the flat region attenuates. These three parameters, $l_{\rm C}$, $g_{\rm L}$, and $g_{\rm R}$, were determined to minimize the discrepancy between the original and approximated functions using the grid search method under the condition that the two functions coincide at the left and right endpoints of the approximated function. When there is no flat region in the original function, $l_{\rm C} = 0$ is satisfied. Figure 4b displays the approximate forms of $f(\Delta_{LR})$ for the original forms appearing in Fig. 3b. (Similar results for all subjects appear in Supplementary Note 3 and Supplementary Fig. 3.) Figure 4c presents the mean and standard deviation of $l_{\rm C}$ among the subjects. It is seen that $l_{\rm C}$ is approximately 0.4 and the deviation among the subjects is small for all perturbation conditions. We confirmed that $l_{\rm C}$ is significantly larger than 0 using one-tailed *t*-test ($p \ll 0.01$, see Supplementary Note 4). Indeed, the mean value of $l_{\rm C}$ is much larger than its standard deviation, and we thus conclude that $l_{\rm C}$ has a positive value. Figure 4d presents the mean and standard deviation of g_L and g_R among the subjects. It is seen that both $|g_L|$ and $|g_R|$ are approximately 2.0, sufficiently large that deviations rapidly attenuate for all perturbation conditions. We also confirmed that $|g_L|$ and $|g_R|$ are significantly larger than 0 using onetailed t-test ($p \ll 0.01$, see Supplementary Note 4). These results confirm that $f(\Delta_{LR})$ has a flat region with a value close to 0 in the vicinity of $\Delta_{LR} = \pi$ and steep negative slopes outside this region for all perturbation conditions.

Discussion

Using time-series data measured during walking under perturbations that disturbed the antiphase relationship between the motion of the left and right legs (Fig. 2), we constructed a function that models the control of interlimb coordination in human walking on the basis of the phase reduction theory and Bayesian inference method. We found that this function has a flat region with values close to 0 in the vicinity of the antiphase condition and steep negative slopes outside this flat region for all subjects studied (Fig. 4). This result indicates that the relative phase between the motion of the left and right legs is not actively controlled until the deviation from the antiphase condition exceeds a certain threshold. In other words, there is a dead zone like that in the case of the steering wheel of an automobile. This differs from our expectation that the relative phase is strictly controlled to maintain the antiphase condition during walking (Fig. 1c). This unexpected finding was obtained for the first time through the quantitative evaluation of the control of interlimb coordination as a function of the relative phase.

Such a forgoing of control implies free for energy cost for the control. This conjectures that the dead zone in the control of interlimb coordination could contribute to energy efficiency during walking. In addition, the forgoing of control induced the relative phase between the legs to be neither exponentially stable nor unstable, but neutral around the antiphase condition (Fig. 3c). Such a neutral stability could enhance maneuverability to

Fig. 2 | Measured and reconstructed time series for one representative subject (Subject G) under mixed conditions. The leg motion, represented by $\varphi_i(t)$ ($i \in (L, R)$), measured during walking was transformed to the oscillator phases $\phi_i(t)$ ($i \in (L, R)$), from which we obtain the relative phase Δ_{LR} . The disturbance of the treadmill belt speed from 1.0 m/s is represented as p(t). The green regions indicate the times at which temporary acceleration or deceleration is applied to the treadmill belt speed.





Fig. 3 | Results for the control of interlimb coordination for one representative subject (Subject G). a Phase sensitivity functions $Z_i(\phi_i)$ ($i \in (L, R)$) for acceleration (Acc), deceleration (Dec), and mixed (Mix) conditions. b Control of interlimb coordination, represented by $f(\Delta_{LR})$. The vertical dotted lines indicate 3 standard deviations from the mean of the observed Δ_{LR} . In the region outside the vertical dotted line, the estimated function $f(\Delta_{LR})$ is displayed in pale color. The function $f(\Delta_{LR})$ is shifted in order to place the mean of the observed values of Δ_{LR} at π to improve visualization. The histogram displays the noise intensity, σ_{LR} . (An expanded histogram, with values 30 times larger than the actual values, is also given.) The

mean and standard deviation of the derived noise intensity for all results are 0.0106π and 0.0021π , respectively. These values are too small to cause deviation of Δ_{LR} from the flat region of $f(\Delta_{LR})$. **c** A schematic diagram for the interpretation of $f(\Delta_{LR})$. The flat region near $\Delta_{LR} = \pi$ at B (neutral stability) and the steep negative slope in the regions away from π reflect the fact that the relative phase between the legs is not actively controlled until the deviation from π exceeds a threshold ($\Delta^A - \pi$ at A and $\Delta^C - \pi$ at C), where motion of the legs deviates significantly from the antiphase relationship.

change the walking behavior. For example, walking along a curved path requires left-right asymmetry in the walking behavior and a phase shift from the antiphase condition³, which conjectures that the lack of control allows a change in the walking direction. However, large deviations from the antiphase condition could result in a deterioration of gait performance. For this reason, it is conjectured that when the deviation exceeds a certain threshold, control is activated to reduce this deviation. Although the slopes of $f(\Delta_{LR})$ outside the flat region vary among the subjects (Fig. 4d), the length of the flat region, which determines the threshold beyond which the control is exercised, does not (Fig. 4c). This result suggests that the threshold is a universal characteristic inherent in the normal walking of healthy young people.

The present result was obtained by determining the specific shape of the function controlling the interlimb coordination. The method employed here relies to a large extent on recent developments in the identification of the phase equation using big data¹⁴. In previous studies^{23,24}, interlimb coordination has also been investigated through use of the phase equation. However, in those works, a simple form (for example a sine function) was assumed for the coupling function in order to determine the function controlling the interlimb coordination. In that case, there appeared no region in which control is not exercised.

The forgoing of control in specific situations in which we expect strict control also appears during quiet standing in humans. Because the upright standing posture is inherently unstable, like an inverted pendulum, it is natural to conjecture that posture is strictly controlled, in order to maintain quiet standing, as we also conjectured that the relative phase of leg motion is strictly controlled in order to maintain the antiphase condition during walking. However, it has been suggested that posture is not actively controlled until deviation from the quiet, upright state exceeds a state-dependent threshold^{25–28}. It is thus conjectured that interlimb coordination during walking and quiet standing have a common motor control strategy in humans.

The leg motion consists of the motion of the thigh, shank, and foot. However, the leg motion is nearly constrained to a two-dimensional space determined by the length and orientation of the limb axis, which connects the hip and toe²⁹. The two-dimensional constraint appears in different speeds³⁰, in other gaits^{31,32}, and in other species³³. In addition, some research has reported that there are neural systems that independently represent the length and orientation of the limb axis in cats^{34,35}, suggesting different controls for the length and orientation of the limb axis. We focused on the control of interlimb coordination only about the relationship between the orientations of the left and right legs, and used the measured time series of the limb axis orientation. As shown in Supplementary Note 5, we confirmed that similar results are obtained from multi-dimensional time series of the legs when we focused on the limb axis orientation. We would like to investigate the control of interlimb coordination about not only the limb axis orientation but also the limb axis length in the future.

As mentioned in the previous paragraph, some studies have suggested that the leg motion can be explained in two-dimensional space. However, it is not completely constrained in two-dimensional space and the part outside of the two-dimensional space could affect the phase. Thus, using multipoint measurements may improve the accuracy of phase calculation compared to the method adopted in the present study, enabling us to reveal phase adjustments in detail. There exist some proposed methods to efficiently identify the phase using multipoint measurements^{20,36}. Using such a method, we conducted a preliminary investigation into the control of interlimb coordination and obtained qualitatively similar results, although the flat region was wider than the result shown in this paper. Determining which method is appropriate for investigating the control of leg motion is highly dependent on the control mechanism of human gait and thus remains a topic for future study. However, our key finding-the existence of a dead zone in the interlimb coordination-remains consistent and robust across the methods we examined. This reinforces the validity and significance of our results regardless of the specific method used.

Because each leg is controlled by the corresponding side of the spinal cord, which has the ability to generate rhythm independently^{37–39}, each leg can operate independently. This independence is manifested in the leg



Fig. 4 | **Characteristics of the control of interlimb coordination, represented by** $f(\Delta_{LR})$. **a** Approximation of $f(\Delta_{LR})$ by a piecewise linear function within 3 standard deviations (3SD) (vertical dotted lines) from the mean of the observed Δ_{LR} . The quantity l_C is the length of the flat region in which we have $f(\Delta_{LR}) = 0$, and g_L and g_R are the slopes in the left and right outside regions, respectively. The three parameters $l_C g_L$, and g_R were determined by the left and right endpoints of the flat region (white circles) such that the discrepancy between the original and approximated functions is minimized within the region between the two vertical dotted lines under the

condition that the approximated function and the original function coincide at the left and right endpoints of the approximated function (black circles). **b** Result for the approximation of $f(\Delta_{LR})$ in Fig. 3b under acceleration (Acc), deceleration (Dec), and mixed (Mix) conditions. **c** Mean and standard deviation of l_C among the subjects, where "All" indicates the statistical result from all perturbation conditions. The dots along the bars represent data points (n = 8 for Acc and Dec, n = 6 for Mix, and n = 22 for "All"). **d** Mean and standard deviation of g_L among the subjects.

during walking changes in elderly people and patients with Parkinson's

disease. We believe that our method will contribute to the understanding of

not only motor control strategies employed by young, healthy humans, but also motor disorder mechanisms in elderly people and patients with neu-

rological disabilities. Finally, we point out that our method derives results

using data measured when the relative phase between the legs recovers after

being disturbed by intermittent perturbations of short duration. Although

we confirmed that reasonable results were obtained from relatively small

amount of measured data in young, healthy humans (see Supplementary

Note 6), more data would be necessary in elderly people and patients with

neurological disabilities. At present, our approach has the limitation that it

does not allow us to increase the number of perturbations within a period

and force subjects to walk for a long time. In the near future, we will improve

our method to reduce the burden on subjects and develop applications for

interaction between the legs. To overcome this difficulty, we varied the belt

speed of the treadmill on which the subjects walked in order to disrupt the antiphase relationship between the legs. In response to such perturbations,

the diagnosis and treatment of gait irregularities.

movements on a split-belt treadmill with the two belts running at different speeds, in which case the legs exhibit asymmetrical left-right stepping^{4,40-42}. Even though each side of the spinal cord can produce rhythmic movement in each leg separately, the motions of left and right legs are generally coordinated during walking. For example, a reciprocal relationship is maintained between the legs such that only one leg enters the swing phase at a time⁴³. Commissural interneurons contribute to interlimb coordination by mediating interactions between the rhythm-generating locomotor circuits located on each side of the spinal cord44-47. We plan to investigate the neural mechanism governing the dead zone in the control of interlimb coordination in future research. In particular, it would be useful to use the phase reduction method¹⁵⁻¹⁸ for a detailed model of the neural system including the musculoskeletal system to derive the two-coupled-oscillator model to evaluate the control of interlimb coordination. The comparison of the results between this theoretical approach and our data-driven approach will provide useful insight into the neural mechanism.

Although the present study focused only on the normal walking of healthy young people, our method has great potential for broader application. For example, because our method can determine the phase coupling functions Γ_{LR} and Γ_{RL} independently, it is applicable to the investigation of the control of interlimb coordination during walking with left-right asymmetry, for example in the case of a curved path³ or a split-belt treadmill⁴, or in the case of hemiplegic stroke patients⁹. In addition, the relative phase between the motion of the left and right legs during walking in elderly people and patients with Parkinson's disease fluctuates significantly^{5–8}. It has been suggested that, unlike young, healthy people, elderly people and patients with Parkinson's disease do exercise strict control in quiet standing²⁴. We plan to investigate how the forgoing of control in interlimb coordination

normal walking of or broader applicathe phase coupling the investigation of ithe left-right asymt-belt treadmill⁴, or the relative phase in elderly people antly^{5–8}. It has been the set of the relative phase in the left and right legs are highly synchronized in the antiphase relationship, and for this reason, the measured data provide little information regarding the set of t

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the control of interlimb coordination was exercised, and this allowed us to extract the phase coupling functions from the measured data. This study was approved by the Ethics Committee of Doshisha University. Written informed consent was obtained from all subjects after the procedures had been fully explained. All ethical regulations relevant to human research participants were followed. A part of the measured data was used in refs. 48,49 for purposes different from that of the present study.

The subjects walked on a treadmill (ITR3017, BERTEC corporation) with a belt speed of 1.0 m/s. We used a motion capture system (MAC3D Digital RealTime System; NAC Image Technology, Inc.) to measure the kinematic data with a sampling frequency of 500 Hz. Reflective markers were attached to the subjects' skin at several easily identifiable positions on both the left and right sides: the head, the top of the acromion, the greater trochanter, the lateral condyle of the knee, the lateral malleolus, the head of the second metatarsal, and the heel. We used the markers at the greater trochanter of the hip and the head of the second metatarsal of the foot to calculate the orientations of the limb axis $\varphi_{\rm L}(t)$ and $\varphi_{\rm R}(t)$ in Fig. 1a. We measured the belt speed of the treadmill using a rotary encoder with a sampling frequency of 500 Hz.

We applied short duration intermittent perturbations to the walking behavior by suddenly changing the belt speed. We used two types of perturbations: temporary acceleration and temporary deceleration. The temporary acceleration and deceleration perturbations increased and decreased the belt speed, respectively, by 0.6 m/s over a period of 0.1 s. The belt speed then returned to the original speed of 1.0 m/s in the following 0.1 s. The perturbations began approximately 10 s after the start of the measurement process and were applied approximately every 5 s thereafter. Each trial included ten perturbations and lasted approximately 60 s. We used three types of perturbation conditions for each trial: acceleration, deceleration, and mixed conditions. Under the first two conditions, only temporary acceleration and deceleration perturbations, respectively, were applied, while under the mixed condition, both types of perturbations were applied randomly.

All subjects (Subjects A–H) were healthy men (n = 8; age 21–23 years; weight 50.2–79.5 kg; height 161–182 cm). Although we recruited participants regardless of gender, no women joined, which would be a drawback. Subjects A and B performed 25 trials under both acceleration and deceleration conditions (with the exception that Subject A performed 24 trials under the deceleration condition). The other six subjects (Subjects C–H) performed 15 trials under each of the perturbation conditions. Each trial consisted of between 805 and 1257 walking cycles in the case of acceleration conditions, between 781 and 1248 walking cycles in the case of deceleration conditions, and between 787 and 852 walking cycles in the case of mixed conditions.

Data processing

In preparation for fitting the various quantities appearing in the phase equation with the measured time-series data, we first transformed the time series of the kinematic angle $\varphi_i(t)$ to those of the oscillator phase, $\phi_i(t)$. (We use the subscript $i \in (L, \mathbb{R})$, which indicates the left or right leg, instead of L and R in the subsequent sections.) In addition, we transformed the time series of the external perturbation p(t) to those for the rescaled external perturbation I(t).

Oscillator phase. First, we obtained the time series for the protophase $\theta_i(t)$ from the time series for the kinematic angle $\varphi_i(t)$ using the Hilbert transform⁵⁰ of $\varphi_i(t)$, $\varphi_i^{\mathcal{H}}(t)$, as

$$A_i(t)\exp(\mathrm{i}\theta_i(t)) = \varphi_i(t) + \mathrm{i}\varphi_i^{\mathcal{H}}(t), \tag{4}$$

where $A_i(t)$ is the amplitude. The phase of an uncoupled limit-cycle oscillator is generally defined in phase reduction theory as always increasing at a constant natural frequency ($\dot{\phi} = \omega$ for phase ϕ and natural frequency ω)^{15–18}. However, the protophase $\theta_i(t)$ in Eq. (4) does not exhibit such a linear time evolution and is not suitable for the phase equation. To statistically rectify this problem, we transformed $\theta_i(t)$ to

 $\phi_i(t)$ as described in refs. 19,51 such that it tends to evolve linearly in time with the natural frequency through the definition

$$\phi_i(\theta_i) = 2\pi \int_0^{\theta_i} g_i(\theta') d\theta', \qquad (5)$$

where $g_i(\theta_i)$ is the probability density function of $\theta_i(t)$ calculated from the time-series data for all trials of the walking experiments for each subject and each perturbation condition. We used $\phi_i(t)$ as the oscillator phase.

External perturbation. To make the phase sensitivity function Z_i a dimensionless quantity, we introduced I(t) through the definition $I(t) = 2\pi p(t)/(\bar{v}\bar{T})$, where \bar{v} is the average treadmill belt speed, \bar{T} is the average gait cycle duration, and $\bar{v}\bar{T}$ is the average stride length for one gait cycle.

Outlier exclusion. Unexpected events during walking, such as stumbling, yields outliers in the derivative of the time series of the oscillator phase. This reduces the accuracy of the fitting. To address this problem, we evaluated the derivative of the oscillator phase at time t_{τ} , v_{τ}^{τ} , as follows:

$$v_i^{\tau} = \frac{\phi_i(t_{\tau+1}) - \phi_i(t_{\tau})}{t_{\tau+1} - t_{\tau}}.$$
(6)

We performed the Smirnov-Grubbs test on the sets of $v_{\rm L}^{\tau}$ and $v_{\rm R}^{\tau}$ to determine the times at which outliers occur (p < 0.05) from the time-series data of all trials. In this procedure, we excluded time series during which external perturbations were applied (green regions in Fig. 2) from consideration. If an outlier appeared at some time t_{τ} the data for $\phi_i(t_{\tau})$ and $I(t_{\tau})$ were excluded from the original data set. Outliers were often detected during touch-down events, when the belt speed exhibited small, sudden variations (Fig. 2).

Fitting the phase equations

Using the time series of the oscillator phase $\phi_i(t)$ and external perturbation I(t), we fit the parameters in the phase equations (Eqs. (1) and (2)) for each subject and perturbation condition. (We obtained 22 sets of results, corresponding to two perturbation conditions for two subjects and three perturbation conditions for six subjects.) Specifically, we obtained values for the natural frequency ω_i , the phase coupling function Γ_{ij} , and the phase sensitivity function Z_i on the basis of the Bayesian inference method^{14,17,21,22}.

Phase coupling function. Because the phase coupling function $\Gamma_{ij}(\psi)$ is 2π -periodic based on the phase reduction theory^{15–18}, it can be represented by a Fourier series as

$$\Gamma_{ij}(\psi) = a_{ij}^{(0)} + \sum_{m=1}^{M_{ij}} \left(a_{ij}^{(m)} \cos m\psi + b_{ij}^{(m)} \sin m\psi \right), \tag{7}$$

where $a_{ij}^{(m)}$ ($m = 0, 1, ..., M_{ij}$) and $b_{ij}^{(m)}$ ($m = 1, 2, ..., M_{ij}$) are coefficients that determine the shape of the phase coupling function, and M_{ij} is the maximum order of the Fourier series. When $M_{ij} = 0$, only the constant term remains, and we have $\Gamma_{ij}(\psi) = a_{ij}^{(0)}$. An appropriate value is necessary for M_{ij} , and it is determined through a model selection, as explained below. To avoid redundancy of the two constant terms ω_i and $a_{ij}^{(0)}$ in Eqs. (1), (2), and (7), we define $\hat{\omega}_i := \omega_i + a_{ij}^{(0)}$ and $\hat{\Gamma}_{ij}(\psi) := \Gamma_{ij}(\psi) - a_{ij}^{(0)}$.

Phase sensitivity function. Because the phase sensitivity function $Z_i(\psi)$ is also 2π -periodic based on the phase reduction theory¹⁵⁻¹⁸, it can be represented by a Fourier series as

$$Z_{i}(\psi) = c_{i}^{(0)} + \sum_{m=1}^{5} \left(c_{i}^{(m)} \cos m\psi + d_{i}^{(m)} \sin m\psi \right),$$
(8)

where $c_{ij}^{(m)}$ (m = 0, 1, ..., 5) and $d_{ij}^{(m)}$ (m = 1, 2, ..., 5) are coefficients that determine the shape of the phase sensitivity function. Because the phase sensitivity function is often composed of lower-order terms, we used a maximum order of 5. We confirmed that the phase sensitivity functions obtained with this restriction were almost identical to those obtained using higher maximum orders up to 10.

Bayesian inference method. Substituting Eqs. (7) and (8) into the phase equations (1) and (2), we obtain

$$\dot{\phi}_{i}(t) = \hat{\omega}_{i} + \sum_{m=1}^{M_{ij}} \left(a_{ij}^{(m)} \cos m\Delta_{ij} + b_{ij}^{(m)} \sin m\Delta_{ij} \right) \\ + \left(c_{i}^{(0)} + \sum_{m=1}^{5} \left(c_{i}^{(m)} \cos m\phi_{i} + d_{i}^{(m)} \sin m\phi_{i} \right) \right) I(t) + \xi_{i}(t),$$
(9)

where $\Delta_{ij} = \phi_j - \phi_i ((i, j) = (L, R), (R, L))$. Then, using the time series of the oscillator phase $\{\phi_i(t_\tau)\}_{i,\tau}$ and those of the external perturbation $\{I(t_\tau)\}_{\tau}$ $(\tau = 0, 1, ..., T)$, where *T* is the sample number for each subject and perturbation condition, we obtain the unknown parameters $\hat{\omega}_i, \{a_{ij}^{(m)}, b_{ij}^{(m)}\}_{i,j,m}, \{c_i^{(m)}, d_i^{(m)}\}_{i,m}, \text{ and } \hat{D}_i (:= \frac{\sigma_i^2}{\Delta t})$, where Δt is the sampling interval. For simplicity, we define the following:

$$\begin{split} \boldsymbol{w}_{i} &:= \left[\hat{\omega}_{i}, \boldsymbol{a}_{ij}^{\mathrm{T}}, \boldsymbol{c}_{i}^{\mathrm{T}} \right]^{\mathrm{T}}, \\ \boldsymbol{a}_{ij} &:= \left[a_{ij}^{(1)}, b_{ij}^{(1)}, a_{ij}^{(2)}, b_{ij}^{(2)}, \dots a_{ij}^{(M_{ij})}, b_{ij}^{(M_{ij})} \right]^{\mathrm{T}}, \\ \boldsymbol{c}_{i} &:= \left[c_{i}^{(0)}, c_{i}^{(1)}, d_{i}^{(1)}, c_{i}^{(2)}, d_{i}^{(2)}, \dots c_{i}^{(5)}, d_{i}^{(5)} \right]^{\mathrm{T}}. \end{split}$$

Here, w_i , whose dimension is N_i (: = 12 + 2 M_{ij}), represents all of the unknown parameters of one phase equation, except for \hat{D}_i , and a_{ij} and c_i represent the unknown parameters of the phase coupling function, $\hat{\Gamma}_{ij}$, and phase sensitivity function, Z_i , respectively.

Following the Bayesian estimation method^{13,14}, we define the likelihood function using a Gaussian distribution \mathcal{N} as follows:

$$P\left(\left\{\phi_{i}(t_{\tau})\right\}_{i,\tau} \middle| \boldsymbol{w}_{i}, \hat{D}_{i}, \left\{I(t_{\tau})\right\}_{\tau}\right)$$

$$= \prod_{\tau=0}^{T-1} \mathcal{N}\left(\boldsymbol{v}_{i}^{\tau} \middle| \hat{\omega}_{i} + Z_{i}(\phi_{i}(t_{\tau}))I(t_{\tau}) + \hat{\Gamma}_{ij}(\Delta_{ij}(t_{\tau})), \hat{D}_{i}\right).$$
(10)

This function represents the probability to reproduce the time series $\{\phi_i(t_{\tau})\}_{i,\tau}$ when the parameters w_i and \hat{D}_i and the time series $\{I(t_{\tau})\}_{\tau}$ are given. We adopt a Gaussian-inverse-gamma distribution \mathcal{IG} for the conjugate prior distribution as follows:

$$P_{\text{prior}}(\boldsymbol{w}_{i}, \hat{D}_{i}) = \mathcal{N}(\boldsymbol{w}_{i} | \boldsymbol{\chi}_{i}^{\text{old}}, \hat{D}_{i} \boldsymbol{\Sigma}_{i}^{\text{old}}) \mathcal{I} \mathcal{G}(\hat{D}_{i} | \boldsymbol{\alpha}_{i}^{\text{old}}, \boldsymbol{\beta}_{i}^{\text{old}}).$$
(11)

Here, the hyperparameters χ^{old} and Σ^{old} determine the mean and covariance matrices, respectively, of the Gaussian distribution \mathcal{N} , and the other hyperparameters, α^{old} and β^{old} , determine the shape and scale, respectively, of the Gaussian-inverse-gamma distribution \mathcal{IG} , which is given by

$$\mathcal{IG}(x|\alpha,\beta) = \frac{\beta^{\alpha}}{\Gamma(\alpha)} x^{-\alpha-1} \exp\left(-\frac{\beta}{x}\right)$$

where $\Gamma(\cdot)$ is the gamma function. In particular, the first element of χ_i^{old} controls $\hat{\omega}_i$, and the other elements control a_{ii} and c_i . In this study, the

hyperparameters in the prior distribution were set as

$$\begin{split} \left(\boldsymbol{\chi}_{i}^{\mathrm{old}}\right)_{k} &:= \begin{cases} \langle \boldsymbol{\nu}_{i}^{\tau} \rangle_{\tau} & k=1\\ 0 & k\neq 1 \end{cases} \\ \boldsymbol{\Sigma}_{i}^{\mathrm{old}} &:= 0.1 \boldsymbol{E}_{i}, \\ \boldsymbol{\alpha}_{i}^{\mathrm{old}} &= \boldsymbol{\beta}_{i}^{\mathrm{old}} = 2, \end{split}$$

where E_i is the $N_i \times N_i$ identity matrix. According to Bayes' theorem, we obtain the posterior distribution of w_i and \hat{D}_i from the product of the likelihood function and prior distribution:

$$P_{\text{post}}\left(\boldsymbol{w}_{i}, \hat{D}_{i} \middle| \{\boldsymbol{\phi}_{i}(t_{\tau})\}_{i,\tau}, \{I(t_{\tau})\}_{\tau}\right) \propto P\left(\{\boldsymbol{\phi}_{i}(t_{\tau})\}_{i,\tau} \middle| \boldsymbol{w}_{i}, \hat{D}_{i}, \{I(t_{\tau})\}_{\tau}\right)$$

$$\times P_{\text{prior}}\left(\boldsymbol{w}_{i}, \hat{D}_{i}\right).$$
(12)

Update rule for hyperparameters. Because of the conjugacy of the prior distribution (Eq. (11)) to the likelihood function (Eq. (10)), the posterior distribution (Eq. (12)) is obtained as a Gaussian-inverse-gamma distribution \mathcal{IG} as follows:

$$P_{\text{post}}(\boldsymbol{w}_i, \hat{D}_i) = \mathcal{N}(\boldsymbol{w}_i | \boldsymbol{\chi}_i^{\text{new}}, \hat{D}_i \boldsymbol{\Sigma}_i^{\text{new}}) \mathcal{IG}(\hat{D}_i | \boldsymbol{\alpha}_i^{\text{new}}, \boldsymbol{\beta}_i^{\text{new}}).$$

Therefore, it is characterized by the hyperparameters χ_i^{new} , Σ_i^{new} , α_i^{new} , and β_i^{new} in the same way as the prior distribution (Eq. (11)).

The update rule for the hyperparameters is derived in a simple way in accordance with the Bayesian update rules. First, we define the matrix $F_i \in \mathbb{R}^{T \times N_i}$ and the vector $\boldsymbol{v}_i \in \mathbb{R}^T$ as follows:

$$F_i := \begin{bmatrix} 1 & (\boldsymbol{g}_i^0)^{\mathrm{T}} & (\boldsymbol{h}_{ij}^0)^{\mathrm{T}} \\ \vdots & \vdots & \vdots \\ 1 & (\boldsymbol{g}_i^{T-1})^{\mathrm{T}} & (\boldsymbol{h}_{ij}^{T-1})^{\mathrm{T}} \end{bmatrix}$$
$$\boldsymbol{v}_i := \begin{bmatrix} v_i^0, v_i^1, \dots, v_i^{T-1} \end{bmatrix}^{\mathrm{T}},$$

where the vectors $\boldsymbol{g}_{i}^{\tau}$ and $\boldsymbol{h}_{ii}^{\tau}$ are given by

$$\boldsymbol{g}_{i}^{\tau} = I(t_{\tau}) \begin{bmatrix} 1, \cos \phi_{i}(t_{\tau}), \sin \phi_{i}(t_{\tau}), \cos 2\phi_{i}(t_{\tau}), \sin 2\phi_{i}(t_{\tau}), \ldots, \cos 5\phi_{i}(t_{\tau}), \sin 5\phi_{i}(t_{\tau}) \end{bmatrix}^{\mathrm{T}}, \\ \boldsymbol{h}_{ij}^{\tau} = \begin{bmatrix} \cos \Delta_{ij}(t_{\tau}), \sin \Delta_{ij}(t_{\tau}), \cos 2\Delta_{ij}(t_{\tau}), \sin 2\Delta_{ij}(t_{\tau}), \ldots, \cos M_{ij}\Delta_{ij}(t_{\tau}), \sin M_{ij}\Delta_{ij}(t_{\tau}) \end{bmatrix}^{\mathrm{T}}.$$

Then, the hyperparameters in the posterior distribution are calculated as follows:

$$\begin{split} \boldsymbol{\chi}_{i}^{\text{new}} &= \boldsymbol{\Sigma}_{i}^{\text{new}} \left(\boldsymbol{F}_{i}^{\text{T}} \boldsymbol{\nu}_{i} + \left(\boldsymbol{\Sigma}_{i}^{\text{old}}\right)^{-1} \boldsymbol{\chi}_{i}^{\text{old}} \right), \\ \boldsymbol{\Sigma}_{i}^{\text{new}} &= \left(\left(\boldsymbol{\Sigma}_{i}^{\text{old}}\right)^{-1} + \boldsymbol{F}_{i}^{\text{T}} \boldsymbol{F}_{i} \right)^{-1}, \\ \boldsymbol{\alpha}_{i}^{\text{new}} &= \boldsymbol{\alpha}_{i}^{\text{old}} + \frac{T}{2}, \\ \boldsymbol{\beta}_{i}^{\text{new}} &= \boldsymbol{\beta}_{i}^{\text{old}} + \frac{1}{2} \left(\boldsymbol{\nu}_{i}^{\text{T}} \boldsymbol{\nu}_{i} + \left(\boldsymbol{\chi}_{i}^{\text{old}}\right)^{\text{T}} \left(\boldsymbol{\Sigma}_{i}^{\text{old}}\right)^{-1} \boldsymbol{\chi}_{i}^{\text{old}} - \left(\boldsymbol{\chi}_{i}^{\text{new}}\right)^{\text{T}} \left(\boldsymbol{\Sigma}_{i}^{\text{new}}\right)^{-1} \boldsymbol{\chi}_{i}^{\text{new}} \right). \end{split}$$

Finally, the unknown parameters w_i and \hat{D}_i of the phase equation (Eq. (9)) are determined from the mean of the posterior distribution.

Model selection. For the phase coupling function (Eq. (7)), we need to choose the model complexity, i.e., an optimal maximum order M_{ij} of the Fourier series. For example, if M_{ij} is too small, there will not be sufficiently many terms to correctly represent the function, whereas if M_{ij} is too large, there will unnecessarily be higher-order harmonic terms involved in

representing the function, and this will lead to overfitting. Following standard Bayesian methods¹³, we determined an optimal value for M_{ij} under the assumption that this value maximizes the model evidence P_{ME} for $0 \le M_{ij} \le 20$ as follows:

$$M_{ij} = \arg_{0 \le M'_{\gamma\nu} \le 20} P_{\rm ME} \Big(\{ \phi_i(t_\tau) \}_{i,\tau} \Big| M'_{\gamma\nu} \Big), \tag{13}$$

$$P_{\rm ME}\Big(\{\phi_i(t_{\tau})\}_{i,\tau}|M'_{\gamma\nu}\Big) = \frac{P\Big(\{\phi_i(t_{\tau})\}_{i,\tau}|w_i,\hat{D}_i,\{I(t_{\tau})\}_{\tau}\Big)P_{\rm prior}(w_i,\hat{D}_i\Big)}{P_{\rm post}\Big(w_i,\hat{D}_i\Big|\{\phi_i(t_{\tau})\}_{i,\tau},\{I(t_{\tau})\}_{\tau}\Big)}.$$
(14)

The values of Δ_{LR} are distributed within a narrow region near π , and the description provided by the phase coupling function is limited to this region. The lack of data outside this region results in the overfitting. Using this method, the optimal value for M_{ij} was determined in each case to be in the range 11–20.

Statistics and reproducibility

We used one-tailed *t*-test to confirm the flat region around the antiphase relationship and the steep negative slopes outside the flat region in the control of interlimb coordination by rejecting that the means of the flat region and the slopes were zero, respectively (n = 22; $p \ll 0.01$). The data points for the *t*-test were obtained by approximating the estimated function of the control of interlimb coordination with a piecewise linear function for each subject and perturbation condition.

Data availability

Source data for graphs presented in the main figures can be found in Supplementary Data. Other data that support the findings of this study are available from the authors upon reasonable request.

Code availability

A sample program (Python code) used in this study is available from the authors upon reasonable request.

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Author contributions

T. Aoyagi and S. Aoi developed the study design. T. Funato performed human experiments. T. Arai and K. Ota analyzed the data in consultation with K. Tsuchiya, T. Aoyagi, and S. Aoi. T. Arai and S. Aoi wrote the manuscript, and T. Aoyagi revised it. All authors reviewed and approved the final version of the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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Correspondence and requests for materials should be addressed to Shinya Aoi.

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