Types of anomalies in two-dimensional video-based gait analysis in uncontrolled environments

Short title: Anomalies in 2D video-based gait analysis

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Abstract

Two-dimensional video-based pose estimation is a technique that can estimate human skeletal coordinates from video data alone. It is also being applied to gait analysis and, particularly, due to its simplicity of measurement, it has the potential to be applied to the gait analysis of large populations. In contrast, it is considered difficult to completely homogenize the environment and settings during the measurement of large populations. Therefore, it is necessary to appropriately deal with technical errors that are not related to the biological factors of interest. In this study, by analyzing a large cohort database, we have identified four major types of anomalies that occur during gait analysis using OpenPose in uncontrolled environments: anatomical, biomechanical, and physical anomalies and errors due to estimation. We have also developed a workflow for identifying and correcting those anomalies and confirmed that the workflow is reproducible through simulation experiments. Our results will help obtain a comprehensive understanding of the anomalies to be addressed in a pre-processing for 2D video-based gait analysis of large populations.

Author summary

Gait is one of the important biomarkers of health conditions. With developing mobile health technologies, it is becoming easier to measure our health. However, to realize preventive medicine, establishing evidence is a critical issue, and we need to collect data from a large population. Two-dimensional video-based pose estimation can be a solution for the gait analysis of such a population. However, the technical accuracy and limitations of this analysis have not yet been sufficiently discussed. In this study, by analyzing the largest database currently available, we systematically identified four types of technical anomalies that occur during gait measurement: anatomical, biomechanical, and physical anomalies and errors due to estimation. We have also shown how to deal with these issues and made solutions available as software so that researchers can reproduce them. In the future, increasing number of studies will use 2D video-based pose estimation to research health-related gait among large populations. We believe that our work will provide a guideline for researchers and clinicians involved in these studies to discuss design and algorithms.

Introduction

Gait is a simple biomarker of the human condition [1], and its effectiveness as a clinical or preclinical marker for diseases such as nervous system abnormalities and skeletal muscle abnormalities has been revealed in various fields [2-6]. In recent years, with the advancement of artificial intelligence applications, several gait analysis methods based on computer vision have been proposed [7-10]. These methods are characterized by the extraction of parameters using images or videos of walking as the input, and two approaches have been proposed to date. One approach is to extract features based on appearance, such as walking silhouette [11, 12], and the other is to extract gait parameters, such as a series of joint positions and joint angles, by fitting and estimating human joint models to the images [13].

One of the algorithms in the latter approach, OpenPose, can estimate joint coordinates at up to 135 key points, such as “body,” “feet,” “hands,” and “face,” for multiple subjects in an image by learning a vector space called Part Affinity Fields (PAF) for associations between anatomical joints based on a deep learning model. Previous research has suggested that the joint estimation capability is sufficient to some extent even in videos with many dynamic factors [14]. Compared with conventional optical motion capture, approximately 80% of the estimated joint coordinates are less than 30 mm with good accuracy [15].

These computer vision-based gait analysis methods can automatically analyze a large number of joint coordinates with only digital video as input and can be used in any environment, including homes and clinics, with little time, cost, and effort compared with conventional optical motion capture. Large-scale human gait analysis can be conducted more easily than before. However, there are some issues to be solved

in applications, such as a certain amount of unexpected noise and the false detection of multiple persons even though one person is walking [16]. In addition, a reproducible and standardized analysis workflow is still lacking. Stenum et al. proposed a comprehensive analysis flow to obtain gait parameters based on OpenPose during gait in a controlled environment [16]. This workflow uses video as input, preprocessing of joint coordinates obtained from OpenPose, and extraction of gait parameters such as step length.

However, the workflow of gait analysis in uncontrolled environments has not been studied sufficiently. To study large populations, a robust approach is needed to capture gait features, even in a heterogeneous environment. Various factors that may affect the accuracy of joint estimation using OpenPose, such as camera performance, the distance between the camera and the subject, walking speed, clothing, and walking environment, are assumed to be involved. Because it is not realistic to control these factors completely, we must address them after the measurement using OpenPose. In a conventional study with a small number of subjects, it may be possible to address the factors manually; however, for a large population of thousands to tens of thousands, such an approach is unrealistic.

To consider the analysis approach in such an uncontrolled environment, it is useful to perform a statistical examination of the error structure based on large-scale data. Fortunately, in recent years, a gait database consisting of 10,307 individuals has been made public using OpenPose technology [17]. This database contains pose estimations for an unspecified number of visitors to a certain facility during walking at 25 flops per second (fps) using a multi-view camera in an uncontrolled manner, and 18 joints are estimated

for one gait cycle [17]. Although the database was originally intended for the biometrics field, we thought it would be possible to investigate technical anomalous errors in uncontrolled environments using this data.

The main purpose of this study was to classify the types of anomalies in pose estimation using OpenPose during the gait cycle in an uncontrolled environment to obtain a roadmap for analyzing large-scale gait data with OpenPose. Through our analysis, we were able to identify four main types of anomalies: anatomical, biomechanical, and physical anomalies and errors due to estimation. In addition, we present a data processing workflow to deal with the errors that we have categorized and demonstrate its reproducibility through simulation experiments. The code used in this study is available on the following website (**URL: <https://github.com/matsui-lab/PoseFixeR>**).

Results

Types of anomalies

Through a comprehensive analysis of the database (Materials and Methods), we classified the main types of anomalous errors to be preprocessed into four categories for the joint coordinates during gait estimated using OpenPose in an uncontrolled environment (Fig 1, Table 1). The four types are anomalies based on anatomical, biomechanical, and physical perspectives and errors due to the inherent estimation accuracy of OpenPose. It should be noted that these types are not completely independent and overlap with each other and, in some cases, are composite. We further subdivided these four categories in terms of

detection and correction methods and finally classified them into ten types that we believe should be considered during analysis (Fig 1).

Fig 1. Types of anomalies during gait using OpenPose. The left panel shows the OpenPose skeletal model

and the name of each part. The right panel shows the anomaly types that correspond to those in Table 1.

Estimation accuracy in Table 1 is excluded from the figure for convenience of illustration. ROM, range of

motion; COG, center of gravity

Table 1. Percentage of each abnormality type.

	ID	Anomaly types	Whole body (18 points)	Only lower limbs (6 points)
Anatomical constraints	a	Undetected parts	97.7	20.5
	b	Leg length	14.8	
	c	Shoulder joint distance	16.1	-
Biomechanical constraints	d	Ankle joint distance	11.6	
	e	Range of motion	69.4	
	f	Center of gravity	6.3	
Physical constraints	g	Time transition	99.7	93.4
	h	Side of legs	29.0	
	i	Grounding	2.1	
Estimation accuracy	j	Reliability	100	43.2

113 The percentages are shown for the 18 parts of the whole body and for the six parts of the lower limbs only.

114 IDs correspond to the right panel in Fig 1.

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116 **Anatomical constraints**

117 Anatomical constraints refer to a series of anomalous errors that could be considered deviations

118 with respect to standard human anatomical constraints (Fig 1a). The most common case observed here was

119 extreme lengthening at the joint located on the opposite side of the camera direction (Table 1). This is

thought to be caused by forcibly making predictions on unobserved joints. In approximately 15% of the subjects, we also observed cases where the shoulder width suddenly increased even though the video was taken from the side (Fig 1c, S3 Fig) and cases where the skeletal length of the lower limbs became extremely short or long before or after a certain point in time, regardless of the camera direction (Fig 1b).

Ideally, we would like to be able to compare the estimated values with the baseline skeletal structure of each person; however, if this is difficult, it may be possible to estimate them by assuming a standard human anatomical skeletal structure and detecting deviations from it. We believe that the relative proportion of standard human skeletal length estimated by a cohort study [18] could be used to determine the expected joint coordinate values in advance. Specifically, if we consider a normalized coordinate with Neck (Ne) as the origin and apply the standard skeletal length (Materials and Methods), we can predict the range within which the joint coordinate values should lie. We used this method to identify joint coordinates that were far outside the normal range (Materials and Methods).

Biomechanical constraints

Anomalous errors deviating from the biomechanical constraints were also observed, mainly in key parameters in the gait analysis, such as the range of motion of the joints (ROM), which is the external angle of the axis connecting Ne and Right Hip (Rh) (or Left Hip [Lh]) and Right Knee (Rk) (or Left Knee [Lk]) (Fig 1d); center of gravity of the trunk (COG) representing the inclination of the trunk (Fig 1e); and stride length with ankle distances (Fig 1f). In particular, the anomalies related to ROM were the highest, accounting

for nearly 70% of all subjects (Table 1), implying the difficulty of biomechanical analysis in uncontrolled environments. It should also be noted that the skeletal model in OpenPose does not exactly match the anatomical skeletal structure (see Discussion).

Furthermore, there are biases in the estimates depending on the distance between the camera and the subject and errors in the pose estimation itself. In fact, when compared with the ROM estimated using a gyro sensor [24], a shift of approximately 10° to 20° was observed, and the variance tended to be large (Fig 2, Table 2). Therefore, instead of directly applying criteria based on other measurement methods, such as gyroscope sensors, OpenPose's baseline should be estimated to separate the signal from the noise. We detected biomechanically unnatural errors by calculating thresholds based on statistical confidence intervals derived from the database (Materials and Methods).

Fig 2. Histograms of ROM of hip and knee joints (left direction: red, right direction: blue). The ranges in red and blue shading are 95% confidence intervals. The black shaded area is the maximum and minimum ROM during gait using inertial sensors as reported by Park et al. ROM, range of motion

Table 2. Mean shift and variability of ROM at the hip and knee joints, comparing published gyro-sensor-based statistics for ROM with those obtained in the present database analysis.

(Unit:deg)	Variable	System	Mean±SD (before anomaly exclusion)	Mean±SD (after anomaly exclusion)
Hip-joint angle (+ flexion / - extension)	Max	OpenPose (R)	27.00±12.40	23.88±8.08
		OpenPose (L)	22.28±9.81	17.27±6.12
		MocapNET	25.70±3.85	25.70±3.85
	Min	OpenPose (R)	-33.07±10.50	-28.35±6.08
		OpenPose (L)	-36.37±11.17	-32.14±5.94
		MocapNET	-14.41±2.23	-14.41±2.23
	ROM	Open Pose(R)	60.06±14.86	52.23±8.96
		Open Pose(L)	58.65±14.60	49.41±7.74
		MocapNET	39.88±3.22	39.88±3.22
Knee-joint angle	Max	Open Pose(R)	64.20±21.83	58.17±9.63
		Open Pose(L)	71.29±20.88	64.43±10.87

(+ flexion / - extension)	Min	MocapNET	64.58 ± 5.21	64.58 ± 5.21
		OpenPose (R)	-4.88±8.29	-1.54±6.24
		OpenPose (L)	-1.10±7.05	0.28±6.26
		MocapNET	-3.18±3.11	-3.18±3.11
	ROM	OpenPose (R)	68.34±19.74	59.71±11.08
		OpenPose (L)	72.39±18.99	64.15±11.98
		MocapNET	67.20±4.66	67.20±4.66

ROM, range of motion; SD, standard deviation

Although COG and stride length anomalies were relatively infrequent, they were distinctly different from the COG and stride length of natural gait and, thus, need to be detected and corrected. In a healthy person, COG is unlikely to fluctuate significantly throughout the gait cycle. We used clustering to identify the positions of the hip (Rh or Lh), knee (Rk or Lk), and ankle (Right Ankle [Ra] or Left Ankle [La]), which were considered to be off-center (Materials and Methods, S1 Fig).

For stride length, we observed cases where the distance of the ankle joint (Ra and La) was underestimated or overestimated for a particular frame or for the entire frame. For the other cases, we focused on the maximum stride length in the gait cycle and derived a threshold based on statistical confidence intervals to identify the error (S2 Fig).

Physical constraints

Gait is a continuous motion in time that depends on the frame rate of the video recording in OpenPose, but it is difficult to imagine instantaneous motion beyond the physical constraints in the normal range. Therefore, motion with extremely discontinuous changes is considered to be due to errors. We considered two types of errors: reversals of the left and right legs (Fig 1g) and discontinuous frame transitions (Fig 1h). In the latter case, it was sufficient to detect the change point in the time series. However, it was not sufficient to detect the case where both legs switched after a certain point; thus, the deviated state was detected using the direction vector in periodic motion (Materials and Methods). Another physically unnatural case is floating from the ground surface (Fig 1i). In this case, the normal range from the head to the ankle was estimated in advance based on the standard human skeletal model [18], and deviations from this range were detected (Materials and Methods).

Estimation accuracy

The reliability score in OpenPose is calculated based on the distance between the correct location and each pixel in the image [19]. Of these, the pixels that are considered to be the shortest distance from the correct location have the highest reliability, whereas a low reliability score suggests that the estimated joint may not exist in the image or that it cannot be estimated. The variability of the actual reliability score tended to be lower for certain joints (Fig 3b). It is not easy to identify the cause of the error due to the reliability score because it is an inherent problem of the deep learning algorithm in OpenPose. However, it is possible to

determine the reliability score from a statistical perspective. The overall distribution of the reliability scores was bimodal (Fig 3a), suggesting the existence of two potential groups of low and high reliability. We estimated these two groups based on k-means clustering and detected the group with low accuracy.

Fig 3. Reliability score. (a) Distribution of reliability scores for all subjects. Two groups, low confidence (blue) and high confidence (red), were assumed and classified by clustering. (b) Reliability score per part. The upper panel is for the left direction, and the lower panel is for the right direction.

Accuracy of pose estimation during gait in an uncontrolled environment

Based on the 10 types of anomalies that we classified, the accuracy of each joint, that is, the percentage of subjects who did not contain those anomalies, was summarized (Fig 4). The accuracy of the joints on the opposite side of the camera direction was low, but on the same side, the accuracy varied, ranging

from 53.8% to 93.5%. In particular, the knee (Rk or Lk) and ankle (Ra or La) contained some anomalous errors in nearly half of the subjects, strongly suggesting that they need to be addressed to perform downstream analysis properly.

Fig 4. Estimated accuracy for each part with OpenPose. The accuracy based on the anomaly types (i.e., the percentage that does not contain any of the anomalies listed in Table 1) is shown. The numbers in parentheses represent the accuracy after correcting the proposed workflow.

Workflow for anomaly detection and correction

To perform gait analysis using OpenPose in an uncontrolled environment, it is necessary to address many anomalous errors during preprocessing. However, it is unclear which strategies should be used for

detection and correction. Here, we present a workflow for detecting and correcting 10 types of anomalies (Fig 5).

Fig 5. Proposed workflow.

Normalization step

The first normalization step transforms the coordinate system and skeletal length into a form that is comparable for all samples. Ne was set as the origin and transformed into joint coordinates corresponding to the ratio of the neck to the trunk length (Materials and Methods). This allows for a general discussion of statistical properties and the setting of thresholds to deal with anomalous errors, which allows for efficient preprocessing.

Anomaly detection step

Following normalization, the anomalous error of switching the left and right legs was first detected and corrected. This is because leg swapping is a serious error in gait analysis and may affect the detection of other anomaly types. Subsequently, the other nine types were detected.

Correction of anomalous error step

The detected parts with anomalous errors could be considered missing values because they cannot be used in the downstream analysis. To some extent, they can be imputed using information from the previous and subsequent frames via averaging. However, if the overall number of missing values is extremely high in one gait cycle or if there are many continuous missing values, the reliability of the missing-value imputation itself is questionable, and such subjects should be excluded. Two filtering criteria were used: (1) the error percentage of each part of the total number of frames was greater than 40%, and (2) the percentage of consecutive missing frames within a gait cycle was more than 20% of the total number of frames (Materials and Methods). Finally, we were able to impute the missing values of 66.8% of the participants.

Other adjustments

In addition, because it has been reported that video-based pose estimation causes distortions in the estimated coordinate values depending on the distance from the camera (Fig 6), and the skeletal length within the same subject is not constant [16], we also corrected the skeletal length (Materials and Methods).

Fig 6. Skeletal length of legs. The left and right panels show the skeletal lengths of the thigh and lower leg, respectively, that depend on the distance between the camera (from the right side) and the subjects. The red and blue represent the right and left sides of the body, respectively.

Reproducibility of workflow

Simulation model

To validate the reproducibility of the workflow in this study, we conducted a simulation experiment based on actual data (S1 Text). The pose estimation by OpenPose during gait can be considered the unobserved true joint coordinates with the addition of the anomalies shown in Table 1. We generated a pseudo dataset for evaluation by adding various errors to the true skeletal coordinates borrowed from real data. The probability of occurrence of each anomalous error was calculated using relative frequencies (Table

1). We generated 10,000 subjects with 25 frames per gait cycle and evaluated the detection accuracy for each anomaly type and the reproducibility of the true joint coordinates.

Simulation results

First, we confirmed the reproducibility of the detection accuracy for individual anomalous errors of the parts; the sensitivity and specificity were 82.6% and 95.1%, respectively. However, the accuracy for each type of anomaly varied from 71.1% to 95.4%, which indicates that the difficulty of anomaly detection varies from joint to joint (Table 3). Pearson's correlation coefficients of the xy-coordinate values before and after the correction were calculated to determine the accuracy for missing imputation, suggesting that there was a significant reproducibility for overall joints (0.770 for the x-coordinate; p-value <2.2e-16, 0.961 for the y-coordinate; p-value <2.2e-16). In addition, the reproducibility of the individual joints was evaluated. Regarding the accuracy at the level of individual joints, there was a tendency for the accuracy to be relatively low for undetected joints, leg length, COG, and ankle distance, which is thought to represent the variability due to the relatively low accuracy of anomaly detection (Table 4).

Table 3. Sensitivity of detection of each type of anomaly by workflow.

Anomaly types	Sensitivity (%)
Undetected parts	73
Leg length	71.1
Shoulder joint distance	85.2
ROM	82.4
COG	79.3
Ankle joint distance	93
Time transition	95.4
Side of legs	88.1
Grounding	89.4

ROM, range of motion; COG, center of gravity

Table 4. Reproducibility of values by workflow.

	Correlation (x-coordinate)	Correlation (y-coordinate)
Undetected parts	0.691	0.935
Leg length	0.767	0.929
Shoulder joint distance	0.768	0.946
Ankle joint distance	0.734	0.922
ROM	0.946	0.943
COG	0.814	0.988
Ankle joint distance	0.734	0.922
Time transition	0.888	0.952
Side of legs	0.657	0.967
Grounding	0.937	0.871

Pearson's correlation coefficient between the true value and the estimated value with correction after performing all the steps of the workflow. ROM, range of motion; COG, center of gravity

Implementation

The workflow presented in this paper has been deposited in Github (<https://github.com/matsui-lab/PoseFixeR>). A series of preprocessing steps were performed using the coordinate values obtained from the posture estimation using OpenPose as the input data. Detailed parameter settings are described in a vignette.

Discussion

We used a large database analysis to comprehensively classify technical anomalies using OpenPose gait pose estimation and identified four main types: anatomical, biomechanical, and physical anomalies and errors due to estimation. We have also shown how to detect these anomalies and suggested a workflow for their correction. According to our criteria, all of the 18 parts estimated by OpenPose contained some anomalies, suggesting that proper pre-processing is required before extracting gait features. Moreover, simulation experiments showed that the accuracy of anomaly detection and correction varied depending on anomaly type, implying the need to develop appropriate preprocessing methods for each type.

In particular, the nature of the two dimensions causes skeletal length distortions dependent on the distance between the camera and the subject, as well as anomalous joint coordinate estimates owing to unobserved joints on the opposite side of the camera direction. The latter anomalous measurement error could be rescued with up to 73% accuracy by our workflow, as shown in the numerical experiments, and it was difficult to capture the complete characteristics of one gait cycle by video recording only on one side.

Therefore, it may be effective to develop an experimental design that focuses on specific parameters, such as the motions of specific joints on the video recording side.

We also need to pay attention to the anatomical skeletal models. In the comparison of inertial sensors and OpenPose in terms of ROMs, we observed a shift of approximately 10° – 20° . One of the main reasons for this is the difference in the skeletal model. Taking the hip joint as an example, in the field of orthopedics and rehabilitation, ROM is generally measured by measuring the external angle composed of the axis between the trunk and femur. However, because the hip joint area is simplified in OpenPose, the ROM is calculated from the external angle composed of the axis directly connecting Ne and Rh/Lh, Rh/Lh, and Rk/Lk, which results in different criteria and generates a bias. Therefore, when analyzing gait using OpenPose, especially when interpreting biomechanical features, we should not simply compare the results with standard sensors, such as gyroscopes and goniometers, but should make comparisons based on OpenPose's baseline.

We showed the anomalies in an uncontrolled environment as comprehensively as possible along with the workflow. However, since the results are based on the analysis of a single database, they do not necessarily cover anomalies at every measurement. It will be necessary to find situations where the two-dimensional video-based pose estimation technique can be used most effectively from a clinical point of view and develop an appropriate analysis algorithm in the future[20]. From a practical standpoint, it is also important to study analysis methods for disease signals through clinical research designs, such as comparisons between healthy and diseased groups. For example, the development of research designs that

focus on specific parts of the body and the research of algorithms that specialize in the early detection of disease-related signatures may be considered to have the same direction. Additionally, the development of open-source software and public databases is also considered to be an important research issue to fill the gap for clinical applications and develop our method as a reproducible research method.

The OpenPose in uncontrolled gait analysis revealed various measurement anomalies in all samples due to technical limitations. However, preprocessing using a combination of anatomical, physical, and biomechanical knowledge and statistical algorithms suggested that nearly 70% of the samples could be rescued, although the accuracy varied for each anomaly type. With the development of appropriate study designs and more sophisticated analysis algorithms in the future, it is expected that accuracy can be improved, even in uncontrolled environments. We hope that our study will be helpful when many studies on large populations are conducted to accumulate evidence.

Materials and methods

Dataset

In this study, we used the Osaka University-Institute of Scientific and Industrial Research (OU-ISIR) Gait Database, a multi-view large population dataset with pose sequences [17] deposited in the OU-ISIR Biometric Database. By capturing the subjects walking approximately 10 m back and forth, we can observe the gait cycle at a normal speed for each sample. The images had a frame rate of 25 fps and an image size of 1280×980 pixels. OpenPose shows the x and y coordinates and confidence levels for 18 joints in

each frame: nose, neck, right shoulder, right elbow, right wrist, left shoulder, left elbow, left wrist, right groin, right knee, right foot, left groin, left knee, left foot, right eye, left eye, right ear, and left ear.

Details of workflow

The details of the workflow are described below. First, we define the mathematical notation. Let $(X_{it}[S], Y_{it}[S])$ be the two-dimensional coordinate value of the joint S of subject $i: i = 1, 2, \dots, N$, at time $t: t = 1, 2, \dots, T$. To represent an arbitrary joint, the name of the joint is written with a dot symbol, as in $(X_{it}[\cdot], Y_{it}[\cdot])$.

Normalization

In video-based pose estimation, normalization is necessary because the skeletal length varies depending on the height of the subject, the distance from the subject, and the position of the camera. In this study, we followed the method described in [17] and normalized the skeletal coordinate values in three steps: (1) centering with the Ne coordinates as the origin, (2) estimating the scale factor of the skeletal length, and (3) normalizing the skeletal coordinates. Specifically, centering was performed using Equation (1).

$$(X_{it}^*[\cdot], Y_{it}^*[\cdot]) = (X_{it}[\cdot], Y_{it}[\cdot]) - (X_{it}[Ne], Y_{it}[Ne]) \quad (1)$$

Next, to calculate the “relative scale” for each individual frame, the distance from the midpoint of the post-transformed coordinates of the left hip $(X_{it}^*[LH], Y_{it}^*[LH])$ and the right hip $(X_{it}^*[RH], Y_{it}^*[RH])$ to the neck $(0, 0)$ was calculated as $scale_{it}$.

$$scale_{it} = \frac{1}{2} \sqrt{(X_{it}^*[LH] + X_{it}^*[RH])^2 + (Y_{it}^*[LH] + Y_{it}^*[RH])^2} \quad \#(2)$$

Finally, we normalized all the joint coordinates such that the relative $scale_{it}$ became 1. That is, each joint coordinate was divided by the relative scale to obtain the normalized coordinates $(X_{it}^+[\cdot], Y_{it}^+[\cdot])$.

$$(X_{it}^+[\cdot], Y_{it}^+[\cdot]) = (X_{it}^*[\cdot], Y_{it}^*[\cdot]) \times \left(\frac{1}{scale_{it}} \right) \quad \#(3)$$

Henceforth, we will use $(X_{it}^+[\cdot], Y_{it}^+[\cdot])$ in the following description.

Anatomical constraints

According to the skeletal length in the standard skeletal model, if the length of the trunk, which is the distance from the neck to the hip joint, is 1, the distance from the neck to the top of the head is 0.5, the distance from the neck to the ankle joint is 2.375, and the distance from the midpoint of the hip joint to the left and right ankle joints is 0.65 [21]. If the x-coordinates of the top of the head and ankle joint, which are the two ends on the y-axis, are the same as the x-coordinates of the neck, the neck coordinates are (0, 0), the head coordinates are (0, -0.5), and the ankle coordinates are (0, 2.375). Therefore, the y-coordinates of all joints were considered to be in the range [-0.5, 2.375]. If the x-coordinate of the midpoint of the hip joint is 0, the length of the ankle joint from the midpoint of the hip joint is 0.65; therefore, the x-coordinates of all joints were considered to be in the range [-0.65, 0.65]. If we introduce an error ratio (ER) to account for individual differences, we can consider that the coordinates of any joint $(X_{it}^+[\cdot], Y_{it}^+[\cdot])$ lie within the following range:

$$-0.65 \times ER \leq X_{it}^+[\cdot] \leq 0.65 \times ER$$

$$-0.5 \times ER \leq Y_{it}^+[\cdot] \leq 2.375 \times ER \quad \#(4)$$

Coordinates that do not satisfy this condition deviate from the expected range.

Biomechanical feature

To identify the joint coordinates deviating from the standard joint angles, 95% confidence intervals were constructed based on the empirical distributions derived from the maximum flexion angles of each joint of the lower extremities (both hip and knee joints) obtained by the following calculations, and those outside the confidence intervals were considered anomalies. First, the Rh flexion angle (calculated in the same way as the Lh flexion angle) was

$$\cos_{it}[RH] = \frac{(X_{it}^+[Ne] - X_{it}^+[RH])(X_{it}^+[Rk] - X_{it}^+[RH]) + (Y_{it}^+[Ne] - Y_{it}^+[RH])(Y_{it}^+[Rk] - Y_{it}^+[RH])}{\sqrt{(X_{it}^+[Ne] - X_{it}^+[RH])^2 + (Y_{it}^+[Ne] - Y_{it}^+[RH])^2} + \sqrt{(X_{it}^+[Rk] - X_{it}^+[RH])^2 + (Y_{it}^+[Rk] - Y_{it}^+[RH])^2}} \quad \#(5)$$

The Rk joint flexion angle (calculated in the same way as the Lk joint flexion angle) was obtained as follows:

$$\cos_{it}[RK] = \frac{(X_{it}^+[RH] - X_{it}^+[Rk])(X_{it}^+[Ra] - X_{it}^+[Rk]) + (Y_{it}^+[RH] - Y_{it}^+[Rk])(Y_{it}^+[Ra] - Y_{it}^+[Rk])}{\sqrt{(X_{it}^+[RH] - X_{it}^+[Rk])^2 + (Y_{it}^+[RH] - Y_{it}^+[Rk])^2} + \sqrt{(X_{it}^+[Ra] - X_{it}^+[Rk])^2 + (Y_{it}^+[Ra] - Y_{it}^+[Rk])^2}} \quad \#(6)$$

From these joint angles, the empirical distribution F was constructed. The joint angles were set as

R_{it} and

$$F(r) = \frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T I(R_{it} \leq r) \quad \#(7)$$

The empirical distribution F for each joint was considered to represent the range of motion distribution in one gait cycle at the population level, including all subjects. Based on this, we constructed a 95% confidence interval $CI_{95\%}$ for each joint and obtained

$$CI_{95\%} = [F^{-1}(0.025), F^{-1}(0.975)].$$

Observed values outside the confidence interval were considered errors.

For the COG error, we considered a point in three-dimensional space consisting of the midpoints in the x-coordinates of the hip (Rh or Lh), knee (Rk or Lk), and ankle (Ra or La) with respect to the perpendicular line from Ne to the ground and identified the group whose distance from the origin deviates by the k-means method. The number of clusters was determined using the gap statistic [22]. The distance *dist* from the origin Ne to a point can be described as follows:

$$dist = \sqrt{\left(\frac{X_{it}^{\dagger}[RH] + X_{it}^{\dagger}[LH]}{2}\right)^2 + \left(\frac{X_{it}^{\dagger}[Rk] + X_{it}^{\dagger}[Lk]}{2}\right)^2 + \left(\frac{X_{it}^{\dagger}[Ra] + X_{it}^{\dagger}[La]}{2}\right)^2} \quad \#(8)$$

For anomalous errors related to ankle joint distance, we used

$$Length_{ankle} = \sqrt{(X_{it}^{\dagger}[Ra] - X_{it}^{\dagger}[La])^2} \quad \#(9)$$

to construct empirical distributions, derive 95% confidence intervals, and detect those outside the intervals as deviating errors. However, because some anomalies in undetected joints may result in extremely large leg lengths, confidence intervals were derived after excluding those errors in advance.

Physical constraints

We describe how to detect the case in which the left and right legs are reversed. The inversion of the leg joint coordinates at frame t was detected by comparing the leg joint coordinates of the two frames before and after. For this purpose, we detected whether inversion occurs at $3 \leq t \leq T - 2$ frames. As we could use time-series information, we removed the effects of missing values and outliers in advance. We

linearly interpolated the knee joint coordinates of vectors $X_t^{\dagger}[La], X_t^{\dagger}[Ra]$ at each frame and then applied spline smoothing to obtain $Z_t[La], Z_t[Ra]$. If the skeletal coordinates measured in one gait cycle are reversed for the left and right legs, the coordinates should not move like a pendulum but should be biased to either the left or right. Thus, one of the following should be true for the inversion of the left and right legs:

$$Y_{it}[Lh] > 1.2 \times 2.283 \text{ and } Y_{it}[Rh] > 1.2 \times 2.283 \#(10)$$

or

$$Y_{it}[Lh] < 0.8 \times 2.283 \text{ and } Y_{it}[Rh] < 0.8 \times 2.283 \#(11)$$

In addition, since it was considered that there is a limit to the movement of the legs during gait,

$$|Z_{it}[La]| < 0.4 \#(12)$$

was assumed to be satisfied. After satisfying these conditions, the direction of the leg joint movement changes after frame t , that is,

$$\text{sign}(Z_{it-2}[La] - Z_{it-1}[La]) = \text{sign}(Z_{it-1}[La] - Z_{it}[La]) = \text{sign}(Z_{it-2}[La] - Z_{it}[La]) \#(13)$$

and

$$\begin{aligned} & \text{sign}(Z_{it}[La] - Z_{it-1}[La]) \\ &= \text{sign}(Z_{it+1}[La] - Z_{it+2}[La]) \\ &= \text{sign}(Z_{it}[La] - Z_{it+2}[La]) \\ &\neq \text{sign}(Z_{it-2}[La] - Z_{it-1}[La]) \#(14) \end{aligned}$$

are satisfied, and the joint coordinates of the left and right legs are considered reversed, where $\text{sign}(\cdot)$ is a sign function.

For the error in ground contact, the reference value of the y-axis coordinates of the legs was set to 2.283. When the y-axis coordinates of both legs deviated sufficiently from the reference value, either upward

or downward, it was determined that the person was not grounded. That is

$$Y_{it}[Lh] > 1.2 \times 2.283 \text{ and } Y_{it}[Rh] > 1.2 \times 2.283$$

or

$$Y_{it}[Lh] < 0.8 \times 2.283 \text{ and } Y_{it}[Rh] < 0.8 \times 2.283. \#(16)$$

The error of the frame transition was defined as more than a certain distance from the coordinate of frame $t-1$ or frame $t+1$. In other words,

$$\sqrt{(X_{it}^+[\cdot] - X_{it-1}^+[\cdot])^2 + (Y_{it}^+[\cdot] - Y_{it-1}^+[\cdot])^2} \geq JUMP$$

or

$$\sqrt{(X_{it}^+[\cdot] - X_{it+1}^+[\cdot])^2 + (Y_{it}^+[\cdot] - Y_{it+1}^+[\cdot])^2} \geq JUMP \#(17)$$

When one or more of the following conditions were satisfied, the joint coordinate was treated as an anomalous error. In this case, JUMP = 0.5 (1/25 s comparison) and 0.7 (2/25 s comparison).

Selecting subjects for imputation

We excluded subjects with many anomalous error frames that we defined because it would be difficult to extract gait features in the downstream analysis. Exclusion criteria were as follows: (1) the error rate of each region was more than 40% of the total number of frames and (2) the missing values were greater than 20% of the total number of frames in one gait cycle (Fig S5). The first criterion was set considering that errors could be detected in at least 20% of samples, even in controlled environments. In addition, technical

errors caused by other factors may occur in uncontrolled environments. For the second criterion, we considered that the maximum percentage of each phase in one gait cycle was approximately 20% [23]

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Competing interests

There are no conflicts of interest.

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Supporting information

Text S1. Details of the simulation.

Fig S1. Detection of a COG anomaly. The left panel shows the coordinate values of (X,Y,Z)=(Ankle, Knee, Hip). The best cluster based on the k-means method using Gap statistic (right panel) is shown by color coding. Clusters very close to the origin were used as normal measurement samples.

Fig S2. Maximum ankle joint distance. Maximum ankle joint distance within one gait cycle for each subject. To illustrate the distribution clearly, skeletal length errors due to undetected sites are excluded.

Fig S3. Distribution of shoulder joint distance. Based on clustering, the four groups were subdivided into four other groups each. The group with slightly larger shoulder joint distance (blue, the third group from the left in the histogram) and the group with extremely large shoulder joint distance (red, the fourth group from the left in the histogram) were considered to have abnormal errors.

Fig S4. Accuracy of anomaly correction. The rate of recovery before and after anomaly correction for each part with workflow. The top and bottom rows show the accuracy for all joints during walking in the right and left directions, respectively, and the left and right rows show the accuracy before and after correction, respectively.

542 **Fig S5. Number of consecutive anomalous frames.** Histogram of the number of consecutive
543 anomaly frames for all samples is shown. The samples with more than 20% consecutive anomalous
544 frames of the total number of frames were excluded.

Fig 1. Types of anomalies during gait using OpenPose. The left p

Fig 2. Histograms of ROM of hip and knee joints (left direction: re

Fig 3. Reliability score. (a) Distribution of reliability scores for all

Direction

Fig 5. Proposed workflow.

Fig 6. Skeletal length of legs. The left and right panels show the s

Fig S1. Detection of a COG anomaly. The left panel shows the co

Fig S2. Maximum ankle joint distance. Maximum ankle joint dist.

Fig S3. Distribution of shoulder joint distance. Based on clustering

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