

A prediction method of speed-dependent walking patterns for healthy individuals

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ABSTRACT

Background: Gait speed is one of the main biomechanical determinants of human movement patterns. However, in clinical gait analysis, the effect of gait speed is generally not considered, and people with disabilities are usually compared with able-bodied individuals even though disabled people tend to walk slower.

Research questions: This study proposes a simple way to predict the gait pattern of healthy individuals at a specific speed.

Methods: The method consists of creating a reference database for a range of gait speeds, and the gait-pattern prediction is implemented as follows: 1) the gait cycle is discretized from 0 to 100% for each variable, 2) a first or second-order polynomial is used to adjust the values of the reference dataset versus the corresponding gait speeds for each instant of the gait cycle to obtain the parameters of the regression, and 3) these regression parameters are then used to predict the new values of the gait pattern at any specific speed. Twenty-four healthy adults walked on the treadmill at eight different gait speeds, where the gait pattern was obtained by a 3D motion capture system and an instrumented treadmill.

Results: Overall, the predicted data presented good agreement with the experimental data for the joint angles and joint moments.

Significance: These results demonstrated that the proposed prediction method can be used to generate more unbiased reference data for clinical gait analysis and might be suitably applied to other speed-dependent human movement patterns.

1. Introduction

Biomechanical patterns of human motion are generally speed-dependent, that is, the amplitude of specific movement typically scales with the movement speed (e.g., walking speed is a determinant factor of the gait pattern) [1,2]. In a typical gait analysis, patients perform gait trials at their comfortable speed and their gait patterns are commonly compared with a reference pattern from a normative database. While this approach may be reasonable, previous studies have reported that individuals with certain pathologies tend to walk slower than able-bodied individuals [3,4]. However, the effect of gait speed is generally not accounted for when the gait pattern of pathological individuals is compared with healthy ones who do not necessarily walk at an equivalent speed.

A possible solution to this problem would be to collect several walking trials at various walking speeds to build a reference database for virtually any possible gait speed. However, the time-consuming nature of such data collection would be cost prohibitive and unviable.

To overcome this challenge, researchers have proposed regression methods as a feasible alternative for predicting gait parameters based on experimental data [5–7]. Those studies predicted gait patterns based only on specific events. Or, when the full gait cycle was considered, the prediction data was based solely on the normal, slow, and fast walking speeds for healthy subjects and only at each 10% interval of the gait cycle [8]. However, because pathological individuals may walk slower than the typical “slow speeds” of healthy subjects, a wider range of gait speeds is likely necessary. In addition, a prediction method for the entire gait cycle at a higher temporal resolution would allow researchers and clinicians to apply standard techniques of analysis commonly employed in the field. In this context, the purpose of this study was to develop a simple way to predict the gait pattern of able-bodied individuals at a given speed, considering a broad range of speeds and the entire gait cycle.

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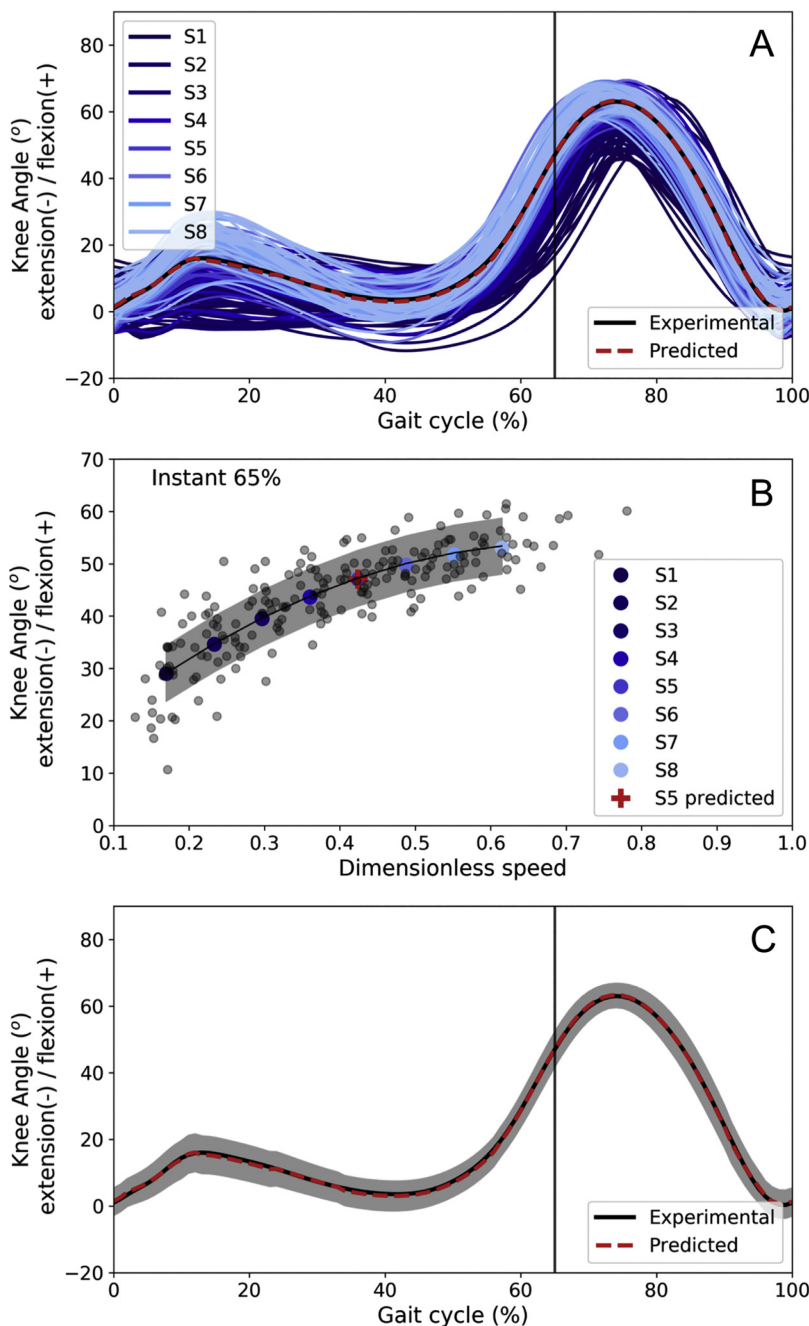


Fig. 1. A. Example of knee angle at the sagittal plane versus the gait cycle of all participants over the range of gait speeds (thin curves). The average pattern of the experimental data across all participants at the self-selected comfortable speed (S5) is displayed by the thick curve and the respective predicted data by the dashed thick curve. The vertical line marks the instant 65% of the gait cycle. B. Knee angle versus the dimensionless gait speed at instant 65% of the gait cycle to illustrate the prediction method. The adjusted curve also shows the predicted values for the eight speeds (filled circles) and the ± 1 SD interval. The experimental values (dots) and the predicted value for the comfortable speed (S5) (plus symbol) are also drawn. C. Average pattern of the experimental data across all participants at the self-selected comfortable speed (S5) (continuous curve) and its respective predicted data (dashed line) with the 68% (± 1 SD) prediction interval (shaded curve).

2. Materials and methods

To nullify the possible effect of speed when comparing a patient's gait with a normative database, we proposed to predict the gait patterns of the reference dataset at the speed of the investigated patient by creating a reference dataset with walking data at different speeds. Then, we determined regression models for the gait patterns with speed as the predictor variable. This prediction method can be implemented with the following procedure:

- 1 Build a reference dataset of the gait pattern acquired at different speeds, ranging from very slow to very fast, and perform the standard signal processing of these data (e.g., see graph A on Fig. 1);
- 2 For each instant of the gait cycle (e.g., 101 instants) of a given kinematic or kinetic variable of each participant, plot the average value across trials (the dependent variable or response) versus the

corresponding dimensionless gait speeds (the independent variable or predictor) (e.g., see graph B on Fig. 1);

- 3 To these data, at each instant for all subjects of the reference dataset, adjust a second-order polynomial using a least-squares method:

$$y(i) = av^2 + bv + c$$

where $y(i)$ represents each kinematic/kinetic variable at instant i , v is the dimensionless walking-speed, and a , b , and c are the coefficients of the regression curve.

- 4 These adjusted curves (e.g., 101 parabolas for the entire gait cycle of each kinematic and kinetic variable) can now be used to predict the new gait cycle value for a given dimensionless speed.

A one-standard-deviation interval (± 1 SD) for the prediction data at each instant (e.g., see graph C on Fig. 1) can be estimated by

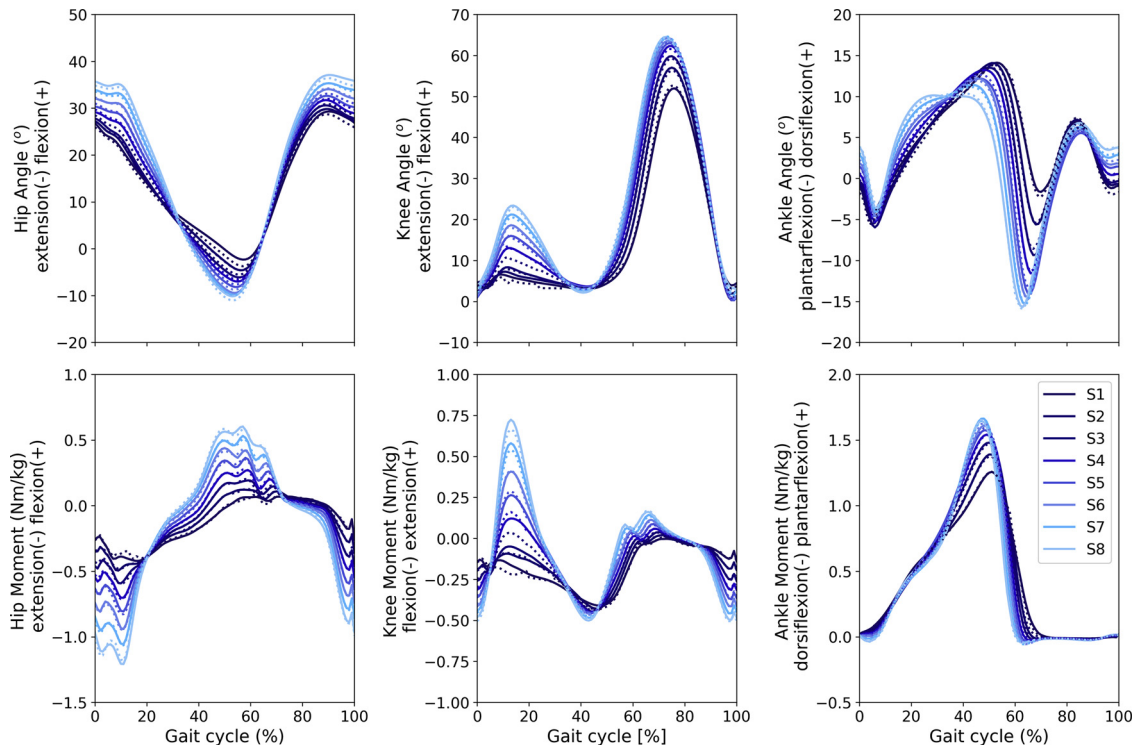


Fig. 2. Average patterns for the joint angles (top) and joint moments (bottom) of the experimental data across all subjects (solid lines) and predicted data (dashed lines) based on the dataset at the different gait speeds.

calculating the 68% prediction interval for the polynomial regression using the equation [9]:

$$PI(i) = t_{68} s_{err} \sqrt{1 + \frac{1}{N} + \frac{(y_i - \bar{y})^2}{\sum_i (y_i - \bar{y})^2}}$$

where t_{68} represents the 68th percentile of the Student's t-distribution with $N-3$ degrees of freedom. N is the number of observations, s_{err} is the standard deviation of the error, and $\bar{y}$ is the mean of y .

The second-order polynomial may in fact not be the best model to fit the data, and a first-order polynomial might be sufficient (however, this was seldom true for the present data). The selection of the order of the polynomial was based on the statistical significance of the coefficient a of the second-order polynomial regression. If this coefficient was not significant (not statistically different from zero), then a first-order polynomial was employed.

2.1. Participants

Twenty-four able-bodied adults (14 males and 10 females; age: 27.6 ± 4.4 years; height: 171.1 ± 10.5 cm; mass: 68.4 ± 12.2 kg) were recruited for this study. All participants were free of any lower extremity injury and presented no history of any orthopedic or neurologic disease.

2.2. Procedures

Each participant performed walking trials in a barefoot condition at different speeds, ranging from very slow to very fast based on their self-selected comfortable speed. Because leg length can affect the walking speed [10], the gait speed was previously adjusted based on the dimensionless speed (the square root of the Froude number). The comfortable speed was obtained based on the average of three overground walking trials at their self-selected comfortable speed along a 10-m walkway. After, each participant walked on a treadmill at his or her self-selected comfortable speed for 5 min. Following this, they walked

at each of the eight controlled speeds in a randomized order: 40%, 55%, 70%, 85%, 100%, 115%, 130%, and 145% of their self-selected comfortable speed. For each walking trial, at each speed, the data were recorded in the last 30 s of the trial. More details about the data collection and procedures are reported by Fukuchi et al. [11].

The biomechanical model of the lower limbs and pelvis adopted was based on a previous protocol proposed for gait analysis [12]. Kinematic data were acquired using a motion capture system with 12 cameras (Raptor-4, Motion Analysis Corporation, Santa Rosa, CA, USA) at 150 Hz, and kinetic data were collected via an instrumented dual-belt treadmill (FIT, Bertec, Columbus, OH, USA) at 300 Hz.

2.3. Data analysis

Marker trajectories and force data were filtered using a fourth-order low-pass Butterworth filter with cut-off frequency of 10 Hz. The kinematic and kinetic curves were time-normalized with 101 points evenly distributed over the gait cycle. The data processing and calculations were performed in Visual3D software (C-motion Inc., Germantown, MD, USA).

2.4. Statistical analysis

A linear or second-order polynomial for the fitting gait variable versus gait speed was adjusted by the least-squares method and a 68% prediction interval (± 1 standard-deviation interval) for the adjusted function was also determined. The validation of the prediction method was done by using the root mean square error (RMSE) as a metric for the accuracy of the prediction comparing the comfortable data with the experimental gait pattern (RMSE c-e), and the experimental data with the predicted gait pattern (RMSE e-p) of the reference dataset. Differences between the two metrics were compared performing Students *t*-test or Mann-Whitney *U* tests ($\alpha = 0.05$). Additionally, 10-fold stratified cross-validation was applied to evaluate the performance of the prediction method and to evaluate its generalizability [13]. For

this, the dataset was divided into ten equal random subsets with nine subsets used to fit the data and the remaining subset was used to test the method.

3. Results

Participants' average walking speeds ranged from 0.13 to 0.78 dimensionless speed (from 0.39 m/s to 2.20 m/s). Fig. 2 shows average patterns of experimental and predicted joint angles and moments across subjects at all eight speeds. Individual curves of the experimental and predicted joint angles and joint moments are plotted in the Supplemental material.

Overall, the predicted data corresponded well to the experimental data for the dataset; the RMSE between the experimental and the predicted data (RMSE e-p) across all speeds, variables, and subjects was $0.48 \pm 0.22^\circ$ for the joint angles and 0.02 ± 0.01 Nm for the joint moments. In contrast, the RMSE between the comfortable and experimental (RMSE c-e) was $2.79 \pm 2.05^\circ$ for the joint angles and 0.10 ± 0.07 Nm for the joint moments. The 10-fold stratified cross-validation presented an accuracy of 96.9% for the joint angles, and 98.6% for the joint moments. The prediction for the gait data of each subject at different speeds was performed based on the average of the entire experimental data (the dataset). We found that the RMSE values were lower for the comparison “experimental data versus predicted data” (RMSE e-p) than for the comparison “comfortable speed versus experimental data” (RMSE c-e) for all the slower walking speeds as well as for walking speeds that were faster than the comfortable speed for the majority of joint angles and joint moments ($p < 0.05$) (Fig. 3; and Table 1 Supplementary material). Individual RMSE values for each joint angle and joint moment graphs are also plotted in the Supplemental material.

4. Discussion

We proposed a simple technique to predict the gait pattern of able-

bodied individuals at a specific speed. This prediction method was validated in two ways. First, we compared the patterns acquired experimentally at different speeds with the predicted pattern for that speed based solely on the data of the same subject (RMSE e-p) (we performed this comparison for 24 subjects). Second, we created a reference dataset with the gait patterns of those 24 subjects and compared with the average of the dataset (acting as a reference dataset) (RMSE c-e). This second comparison mimics a real scenario where a reference gait dataset is available, and one wants to compare these data with the experimental data of a patient likely evaluated at a different gait speed (in the present case, each subject of the dataset acted as an experimental subject versus the control given by the entire dataset).

The method we proposed to predict the gait pattern at a given speed presented good agreement with the experimental data of each subject for the joint angles and joint moments in a range of speeds from 0.39 m/s to 2.20 m/s. The greater the difference in gait speed between the reference dataset and the experimental data, the greater the difference between the predicted data and the reference dataset without the prediction. The prediction method proposed, seems to mitigate the effects of the gait speed especially at lower speeds in some subjects, but did not totally nullify them. Thus, future study with a larger sample is needed to improve this method.

Compared with the present study, previous prediction methods were based on specific gait events (e.g., peaks) [5–7] or on walking data acquired either at the comfortable speed [7] or only at comfortable, slow, and fast speeds [6,8]. One study employed a prediction method based on the entire curve at each 10% interval of the gait cycle by applying a linear regression method [8]. However, only a linear regression prediction method was implemented, which was different from the quadratic regression used in the present study.

Given the characteristics of the prediction method proposed, the range of speeds used to build the dataset must include the speed at which one wishes to predict; the proposed method can only perform interpolation, not extrapolation, to predict the pattern. To parameterize the relation between the amplitude of motion and gait speed, a linear or

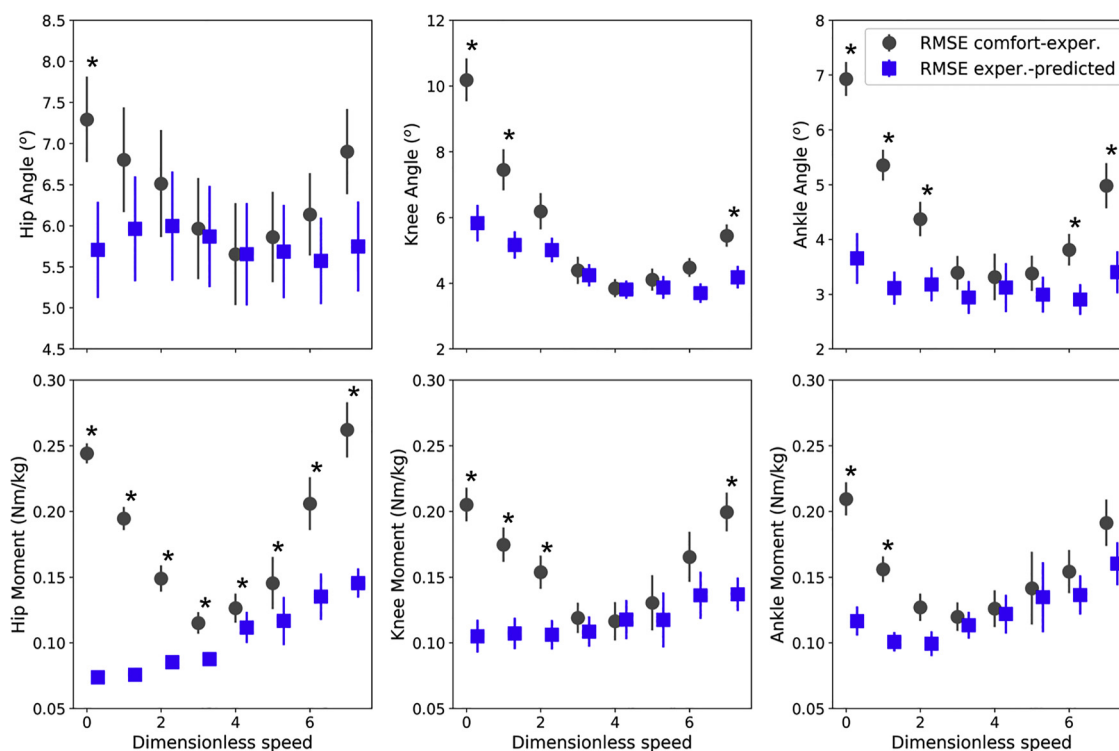


Fig. 3. RMSE values (mean $\pm$ 1 standard error of the mean) across subjects of the joint angles and moments at the sagittal plane for the comparisons “comfortable speed versus experimental data” at different speeds (comfort-exper., circles) and “experimental versus predicted data” (exper.-predicted, squares).

a second-order polynomial function was chosen. Overall, the relationship between the kinematic and kinetic variables and speed were typically non-linear. The parabola is a convenient mathematical function able to capture the observed nonlinearities, and it has only three parameters for adjustment. Nevertheless, another function for adjustment could be used as long as this function can capture the behavior of the data.

To make the prediction method more accessible, we prepared two Excel spreadsheets as supplementary material. The Adults.xlsx in Supplemental material spreadsheet contains the equations derived from the present data to predict the gait patterns at any gait speed (reliable for a range of 0.13 to 0.78 dimensionless speed). The Children.xlsx in Supplemental material spreadsheet contains the prediction equations derived from data in the Schwartz and collaborators [1] study of children with an average age of 10.5 years walking at five different speeds. Since previous studies stated that walking speed and not age is the main determinant of the gait pattern in this population [1,2], this range of speed would be necessary to understand this condition better. Contrary to this, as age has been reported to influence the gait pattern in children with an average age of 3.6 years [14], the gait pattern in younger children that is not matured yet seems to be more affected at a greater extent by age than speed. Nevertheless, future study should further explore the relative contribution of age on the gait pattern.

In summary, the proposed technique successfully predicted speed-specific joint angles and joint moments patterns in able-bodied individuals for any gait speed. This prediction reduces the difference compared with the reference dataset since it compares the experimental gait pattern with the predicted one at the same gait speed. This method may be adapted to generate a more unbiased reference normative data to be used to evaluate the gait pattern of pathological individuals, or it may even be suitable for application to other speed-dependent human movement patterns.

Declarations of interest

None.

Conflict of interest statement

None.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <https://doi.org/10.1016/j.gaitpost.2018.12.006>.

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