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# Gait Profile Score in able-bodied and post-stroke individuals adjusted for the effect of gait speed

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ABSTRACT

Background: The Gait Profile Score (GPS) measures the quality of an individual's walking by calculating the difference between the kinematic pattern and the average walking pattern of healthy individuals.

Research questions: The purposes of this study were to quantify the effect of speed on the GPS and to determine whether the prediction of gait patterns at a specific speed would make the GPS outcome insensitive to gait speed in the evaluation of post-stroke individuals.

Methods: The GPS was calculated for able-bodied individuals walking at different speeds and for the comparison of post-stroke individuals with able-bodied individuals using the original experimental data (standard GPS) and the predicted gait patterns at a given speed (GPS velocity, $GPS^v$). We employed standard gait analysis for data collection of the subjects. Sixteen participants with a stroke history were recruited for the post-stroke group, and 15 age-matched, able-bodied participants formed the control group.

Results: Gait speed significantly affects the GPS and the method to predict the gait patterns at any speed is able to mitigate the effects of gait speed on the GPS. Overall, the gap between the GPS and $GPS^v$ values across the post-stroke individuals was small (0.5° on average, range from 0.0° to 1.4°) and not statistically significant. However, there was a significant negative linear relationship in the absolute difference between the GPS and $GPS^v$ values for the participants of the post-stroke group with gait speed, indicating that a larger difference between the speeds of the post-stroke participant and the reference dataset resulted in a larger difference between the GPS and $GPS^v$.

Significance: The modified version of the GPS, the $GPS^v$, is effective in reducing the impact of gait speed on GPS; however, the observed difference between the two methods was only around 1° for the slowest individuals in comparison to the reference dataset.

## 1. Introduction

The Gait Profile Score (GPS) measures the quality of an individual's walking by calculating the difference between the kinematic pattern (angles for the pelvic tilt, obliquity, and rotation; and for both sides of the body, hip flexion, abduction and rotation, knee flexion, ankle dorsiflexion, and foot progression) and the average walking pattern of healthy individuals [1]. Compared with other gait indices, such as Gait Deviation Index [2], Gait Deviation Index Kinetic [3], and Gillette Gait Index [4], GPS has the advantage of also revealing the separate contribution of each kinematic variable (angles for the pelvic tilt, obliquity, and rotation; and for both sides of the body, hip flexion, abduction and rotation, knee flexion, ankle dorsiflexion, and foot progression) by first calculating the Gait Variable Score (GVS), thereby creating the Movement Analysis Profile (MAP). The GPS has been used to evaluate gait abnormalities in different populations [5–7]. In such evaluations, comparisons are made between one or more patients and a dataset of healthy individuals walking at their comfortable pace at speeds typically higher than the patients. A likely problem with this approach is that it is known that walking speed affects gait patterns of healthy individuals [8,9] and for instance, people with a stroke history [10–14] or with Parkinson's disease [15] tend to walk slower than healthy controls. In fact, gait speed, not age, has been suggested to be the primary determinant of kinematic and kinetic alterations in children [16]. Therefore, the GPS would be influenced by either the physical condition (the pathology per se) or the walking speed, or both, potentially hampering the ability of the GPS to quantify the exact effect of a disorder on the gait pattern. When the GPS was correlated with walking speed, only a small correlation (ρ = 0.28) was found [1]. However, since these data were predominantly from individuals with different disabilities or at

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distinct stages of impairment, these factors alone may have confounded the effect of speed on the gait patterns. I.e., ideally, a study where the same subjects walk at several different speeds would be more appropriate to capture the effect of speed on the gait patterns.

Previous studies have proposed methods to lessen the effect of walking speed on gait [16–20]. For instance, Schreiber et al [17] proposed a method where a correction for the effect of speed is introduced directly on the computation of the gait indices rather than on the gait patterns and they demonstrated the validity of the method on a healthy population. Another method proposed elsewhere [16,18,17–20] is to estimate the patterns at a given speed using regression methods to predict the new data based on a dataset of experimental data and then using the estimated patterns in the calculation of the gait indices. A regression method for gait-pattern prediction at a specific speed recently proposed has the advantage of being able to predict the entire pattern for the gait cycle successfully [20]. While this method has been tested on a broad range of gait speeds for healthy individuals, it hasn't yet been applied to a clinical context; neither has it been used to make the GPS outcome insensitive to gait speed. In this context, we designed a study where we applied the GPS to evaluate the gait of able-bodied individuals walking at different speeds, and individuals with stroke histories walking at their comfortable speed. The GPS was calculated for the comparison of post-stroke individuals with able-bodied individuals using the original experimental data (standard GPS) and for the comparison with the predicted gait patterns at the speed of the post-stroke individuals (referred to here as Gait Profile Score velocity, $GPS^v$). Since the $GPS^v$ compares the individual's gait pattern with speed-adjusted gait pattern, rather than with an average control group gait pattern as employed in the standard GPS, we hypothesize that the proposed $GPS^v$ will lessen the effect of gait speed compared to the standard GPS.

## 2. Methods

### 2.1. Participants

Sixteen participants who had stroke histories (8 males, age: 66.9 ± 7.0 years, height: 168.6 ± 7.2 cm, mass: 65.5 ± 7.5 kg; and 8 females, age: 60.1 ± 11.4 years, height: 155.4 ± 5.7 cm, mass: 67.0 ± 12.3 kg) were recruited for the post-stroke group. There were six individuals with left hemisphere stroke (right paretic) and ten with right hemisphere stroke (left paretic), of which, 12 ischemic and 4 hemorrhagic and with a mean time after stroke of 76.8 months. Inclusion criteria were that they: 1) had experienced a single stroke episode at six months or more prior to the data collection, 2) could walk at least 10 m without any type of assistance, 3) had no history of any musculoskeletal disorders that could substantially impact the gait pattern, and 4) were able to understand experimental tasks. A control group was formed with 15 age-matched, able-bodied participants (6 males, age: 59.7 ± 6.1 years, height: 168.7 ± 3.9 cm, mass: 74.9 ± 8.2 kg; and 9 females, age: 58.9 ± 5.8 years, height: 159.6 ± 11.4 cm, mass: 63.9 ± 14.6 kg). These participants were free of any orthopaedic or musculoskeletal injury in the six months before the data collection and had no history of neurologic disease. All participants read and signed a consent form approved by the local University.

### 2.2. Construction of the reference data

To predict the kinematic patterns of the reference dataset at a certain speed, data collection of able-bodied subjects walking at a range of gait speeds was required to later interpolate the gait patterns at any desired speed within this range based on the method previously proposed [20]. For such, we had to employ a treadmill to specify and control these different speeds because subjects could not reproduce overground walking trials at so many varied speeds. However, most of the older adults we evaluated who had stroke histories were unable to walk independently on a treadmill. Given that and to avoid a direct overground-treadmill gait comparison between different populations, which would introduce another confounding factor into our group comparison, we adopted a hybrid procedure to create the reference dataset with a range of gait speeds. We collected data for able-bodied subjects walking on the treadmill at different speeds as well as overground at their comfortable speed. Then, for each kinematic variable ($X$) of an able-bodied subject walking at each speed on the treadmill ($vi$) ($X_{\mathrm{Vi@treadmill}}$), we subtracted its mean value at the comfortable speed on the treadmill ($\bar{X}_{\mathrm{Vcomf@treadmill}}$) and added its mean value at the comfortable speed on overground ($\bar{X}_{\mathrm{Vcomf@overground}}$). That is, we simply shifted the values on the treadmill by a constant value based on a possible variation between the two environments at the comfortable speed, mathematically:

$$X_{Vi@treadmill-overground} = X_{Vi@treadmill} - \bar{X}_{Vcomf@treadmill} + \bar{X}_{Vcomf@overground}$$

This reference data is designated as a treadmill-overground dataset (see Fig. 1 in the Supplementary material for an example of data before and after this procedure).

### 2.3. Data acquisition

We employed standard gait analysis procedures for data collection using a motion capture system with 1) 12 cameras (Raptor-4, Motion Analysis Corporation, Santa Rosa, CA, USA); 2) five force platforms (three 40 × 60 cm model Optima, AMTI, Watertown, MA, USA; two 40 × 60 cm model 9281 EA, Kistler, Switzerland) embedded on the floor; and 3) a dual-belt instrumented treadmill (FIT, Bertec, Columbus, OH, USA) in a 10 × 12 m room at the Laboratory of Biomechanics and Motor Control, Federal University of ABC, Brazil. Kinematic data were acquired at 150 Hz, and the ground reaction force data were acquired at 300 Hz by the motion capture system (Cortex 6.0, Motion Analysis Corporation, Santa Rosa, CA, USA). For this study, ground reaction forces data were used for gait event detection purposes. Before the data collection, leg length (defined as the distance from the anterior superior iliac spine [ASIS] to the ipsilateral medial malleolus), mass, and stature of each participant were measured. Twenty-six retro-reflective markers were attached to the pelvis and lower limbs according to a biomechanical model previously described [20,21].

For the control group, to define the comfortable speed, each participant performed three walking trials barefoot at their comfortable speed along a 10-m flat walkway. The mean gait speed was calculated and then normalized based on the participant's leg length [22]. Following this, each participant performed at least five walking trials at their comfortable speed, and these data were used in further analysis. For a more reliable gait evaluation at different speeds, we also asked each participant in the control group to walk on an instrumented treadmill. First, they walked for 5 min at their previously defined and self-selected comfortable speed. Next, they walked at each of the eight different controlled speeds (40%, 55%, 70%, 85%, 100%, 115%, 130%, and 145% of their self-selected speed) in a randomized order for 90 s where the data were recorded in the last 60 s of the trial. For the post-stroke group, each participant walked barefoot only at their comfortable speed on a 10-m walkway.

### 2.4. Data analysis

Kinematic and kinetic data were filtered with a fourth-order low-pass Butterworth filter and a cut-off frequency of 10 Hz. The definition of the segment anatomical reference frames was performed according to Leardini et al. [21]. The 15 kinematic variables proposed on the GPS [1] were calculated: angles for the pelvic tilt, obliquity, and rotation; and for both sides of the body, hip flexion, abduction and rotation, knee flexion, ankle dorsiflexion, and foot progression. Kinematic time-series curves were time-normalized with 51 points over the gait cycle, and the data were processed in Visual3D software (C-motion Inc., Germantown, MD, USA). We calculated the time-normalized ensemble average across participants at their comfortable speed to serve as the reference dataset. The GVS was computed as the root-mean-square (RMS) difference between the participant's speed and the average from the reference dataset for each of the kinematic variables. Then, the GPS was computed as the RMS average of all the GVS values [1].

We predicted the kinematic patterns of the reference dataset for the participant's speed based on a regression method previously described [20] using the following steps. First, we adjusted a first or a second-order polynomial (based on the goodness of fit) to 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. Second, we employed these regression parameters to predict the new values of the gait pattern at any specific speed. The GVS and GPS values were then calculated on these speed-adjusted data and are referred to as $GVS^v$ and $GPS^v$, respectively.

### 2.5. Statistical analysis

Descriptive statistics of the dependent variables are presented as a mean and standard deviation. Shapiro-Wilk's tests were applied to examine the normal distribution for both GVS/$GVS^v$ and GPS/$GPS^v$ methods. To determine the difference between groups, either Student's *t*-test or the non-parametric Mann-Whitney test was applied when the normality assumption was not found. Additionally, we calculated the absolute difference between GPS and $GPS^v$ methods and then, we verify the relationship of it with the dimensionless speed. For that, the Pearson correlation coefficient and linear regression by least squares were calculated. The adjusted correlation coefficient and the 68% prediction interval were also calculated for the fits. A statistically significant difference was considered for a $p$-value $< 0.05$.

## 3. Results

Gait speed at the comfortable condition for each subject in the control and post-stroke group is described in Table 1. For the control-group subjects, the GPS index presents a non-linear relation with gait speed ($r = 0.45$, $p < 0.001$; see Fig. 1). However, there is a significant variation between subjects for the GPS vs. speed. Once part of this between-subject variability is removed by computing only the change of GPS for each subject at different speeds in relation to the GPS at the comfortable speed (ΔGPS), the non-linear relationship between speed and GPS is more pronounced ($r = 0.79$, $p < 0.001$). When we employ the prediction method to adjust the reference data for the difference in speed, the effect of speed is mitigated for both the $GPS^v$ and $\Delta GPS^v$ (see Fig. 1).

**Table 1**
Comfortable speed (m/s) of each subject in the control and post-stroke groups.

| # subject | Control | Post-stroke |
|---|---|---|
| 1 | 1.01 | 1.02 |
| 2 | 1.20 | 1.27 |
| 3 | 1.33 | 0.39 |
| 4 | 1.45 | 0.70 |
| 5 | 1.44 | 0.55 |
| 6 | 1.10 | 0.65 |
| 7 | 1.10 | 1.19 |
| 8 | 1.30 | 0.51 |
| 9 | 0.98 | 0.65 |
| 10 | 1.28 | 0.68 |
| 11 | 1.41 | 1.11 |
| 12 | 1.33 | 0.62 |
| 13 | 1.19 | 0.58 |
| 14 | 0.91 | 0.98 |
| 15 | 1.27 | 1.03 |
| 16 | – | 0.71 |

On average, the post-stroke group walked at a comfortable gait dimensionless speed slower than the control group (stroke: $0.28 \pm 0.09$, control: $0.42 \pm 0.06$; $d = 1.86$, $p < 0.001$). For example, Fig. 2 shows plots of the knee flexion angle for the gait cycle of a post-stroke participant compared with the same variable from the experimental reference data at the comfortable speed and the predicted speed-dependence variable for this post-stroke participant. Table 2 shows the average gait variable score (GVS and $GVS^v$) across subjects of each group (plots with the individual values per subject can be found in the Supplementary material to this article). When comparing the post-stroke with the control subjects as a whole, none of the differences between the GVS and $GVS^v$ values were statistically significant, nor were the overall differences between the GPS and $GPS^v$ values (GPS: $8.0 \pm 3.1°$, $GPS^v$: $7.7 \pm 3.2°$; $d = 0.10$, $p = 0.774$). However, a negative correlation between the absolute difference in the GPS and $GPS^v$ values for the participants of the post-stroke group and the gait speed was observed ($\rho = -0.63$, $p = 0.009$, see Fig. 3).

Fig. 4 shows the Movement Analysis Profile for the post-stroke participant with the largest absolute difference between the two techniques ($v = 0.19$ dimensionless gait speed). The greatest difference for this participant between the GVS and $GVS^v$ values was for the left knee angle (5.1°), and on average across all variables, the absolute difference between the GPS and $GPS^v$ values was 1.5°.

## 4. Discussion

The purpose of this study was to investigate the effect of gait speed on the GPS of post-stroke individuals who tend to walk slower than typical able-bodied subjects, employing a technique for predicting the gait patterns of the able-bodied subjects at the similar speeds of the post-stroke individuals for the comparison. The method for the prediction of gait patterns at a specific speed was successfully tested in controlled conditions with able-bodied subjects walking at different speeds [20].

The relationship between gait speed and the GPS index for the control-group subjects, where each one walked at different speeds ranging from very slow to very fast, is nonlinear, and a concave-upward parabola with a minimal GPS value captured it at the subject's comfortable speed. Such nonlinear dependence hasn't been described before and serves as an awareness for the application of linear methods to investigate the relationship between gait speed and biomechanical variables.

The GPS index has been widely used as a measure of the overall gait pattern. It has been applied to different clinical conditions [1,5,6,23–26] including post-stroke individuals [27]. However, they were either studies comparing the walking pattern of pathological individuals with healthy controls walking at their self-selected comfortable speed [1,5,6,23,24] or assessing the reliability of GPS [27]. Given that pathological individuals tend to walk slower than healthy people, the results of these studies may be biased since it is not possible to determine whether the differences were due to gait impairment or only because of gait speed differences. In the present study, individuals in the post-stroke group walked slower than healthy controls. Previous studies have reported a slower gait speed in post-stroke individuals compared with healthy ones, but the comfortable walking speed of the post-stroke individuals in the present study was 0.80 m/s (range: 0.39–1.27 m/s), which was more extensive than reported in other studies for individuals with a similar clinical condition: on average, 0.44 m/s and 0.56 m/s [13,14]. The larger comfortable speed of the post-stroke individuals investigated here is likely because individuals in the present study had their stroke episodes a longer time ago (on average 76.8 months) than the individuals of those studies (median of 31 days [13] and mean of 36.4 months [14]).

We hypothesized that the proposed $GPS^v$ would be less affected by the difference in gait speeds between groups than the standard GPS. Overall, the difference between the GPS and $GPS^v$ across the post-stroke

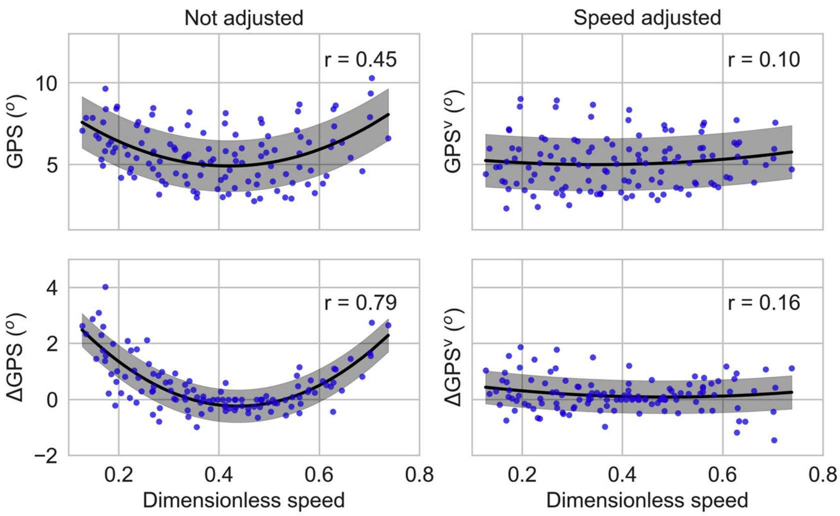


**Fig. 1.** GPS (top graphs) and the change in the GPS in relation to its value at the comfortable speed (ΔGPS, bottom graphs) for the not adjusted (GPS, left graphs) and speed adjusted (GPS$^v$, right graphs) versus dimensionless speed for all participants and gait speeds in the control group. Also shown are 1) the least-square fit by a parabola (thick line), 2) the 68% prediction interval (shaded area), and 3) the adjusted coefficient of correlation for the fit (r).

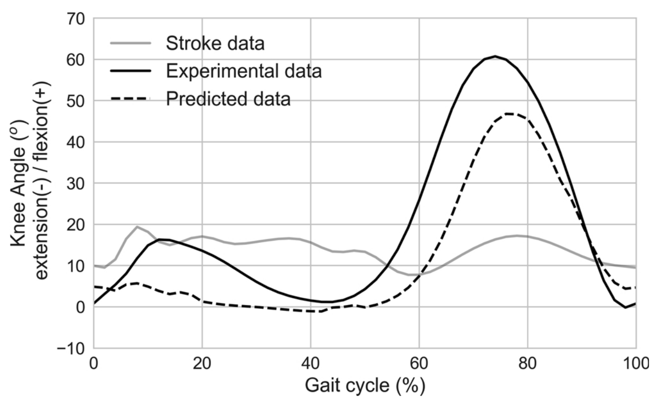


**Fig. 2.** Example of the variable knee flexion angle for the post-stroke participant with the slowest gait speed (Stroke data: v = 0.13, grey line) compared with the data from the database at the comfortable speed (Experimental data: v = 0.42, solid line) and the data after the speed-dependent prediction (Predicted data: v = 0.13, dashed line). The GVS and GVS$^v$ for this variable are then calculated based on the RMS difference between the two corresponding curves.

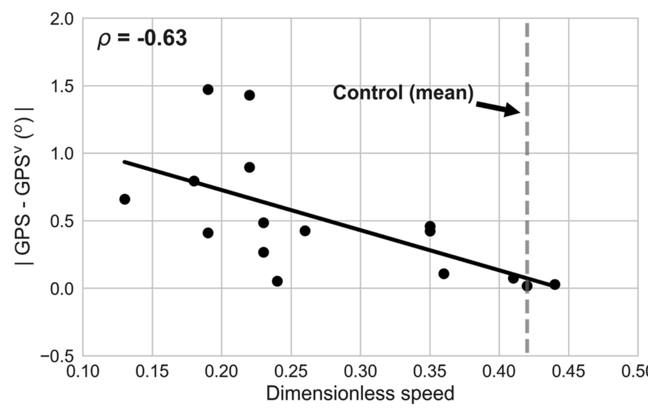


**Fig. 3.** Absolute difference between the GPS and GPS$^v$ values versus the dimensionless speed for all participants in the post-stroke group. The vertical dashed line represents the mean gait speed of the control group.

individuals was small (0.50° on average, range from 0.02° to 1.43°) and not statistically significant, contrary to our hypothesis. However, a subject-by-subject analysis revealed that the participants of the post-stroke group were very heterogeneous regarding their comfortable speed; some of them even presented similar speeds to the control group.

There was also a significant negative linear relationship between the absolute difference of the GPS and GPS$^v$ values for the participants of the post-stroke group with gait speed (Fig. 3, $\rho = -0.63$, $p = 0.009$). A similar relationship was observed for the individuals in the control group at both ranges of slower and faster speeds than the comfortable speed (Fig. 4, Supplementary material). This indicated that a greater difference between the speeds and the normative database resulted in a greater difference between the GPS and GPS$^v$ values, which is in agreement with our hypothesis. For instance, the differences between GPS and GPS$^v$ for the individuals in the post-stroke group with the slowest speeds ranged between 0.4° and 1.47° (see the Movement Analysis Profile in Fig. 4 for the post-stroke individual with one of the slowest gait speeds, v = 0.19 dimensionless speed or 0.55 m/s, with a difference of about 1.4°).

The computation of both GPS and GPS$^v$ might also be useful to understand how the gait patterns of individuals with gait abnormality

**Table 2**
Mean ( ± 1 SD) across subjects of the GVS and GVS$^v$ values for the right and left sides and the corresponding effect size (*d*) and *p*-value for the statistical test.

| Variable [°] | Right side | | | Left side | | |
|---|---|---|---|---|---|---|
| | GVS | GVS$^v$ | *d, p* | GVS | GVS$^v$ | *d, p* |
| Pelvic tilt | – | – | – | 5.2 ± 3.4 | 5.1 ± 3.2 | 0.04, 0.910 |
| Pelvic obliquity | – | – | – | 3.2 ± 1.4 | 2.8 ± 1.4 | 0.30, 0.133 |
| Pelvic rotation | – | – | – | 5.4 ± 5.0 | 5.6 ± 4.8 | −0.03, 0.346 |
| Hip flexion | 10.1 ± 5.6 | 9.0 ± 5.3 | 0.20, 0.255 | 8.0 ± 3.8 | 7.6 ± 3.9 | 0.10, 0.771 |
| Hip adduction | 6.4 ± 2.7 | 4.9 ± 2.5 | 0.56, 0.127 | 3.8 ± 1.6 | 3.7 ± 1.7 | 0.02, 0.492 |
| Hip rotation | 8.4 ± 7.8 | 8.6 ± 8.1 | −0.02, 0.462 | 8.3 ± 4.1 | 8.0 ± 4.6 | 0.07, 0.855 |
| Knee flexion | 7.6 ± 3.4 | 7.3 ± 3.6 | 0.08, 0.827 | 10.2 ± 5.0 | 9.6 ± 4.3 | 0.12, 0.731 |
| Ankle dorsiflexion | 5.3 ± 3.5 | 5.1 ± 3.4 | 0.05, 0.433 | 5.6 ± 2.2 | 4.8 ± 2.7 | 0.30, 0.068 |
| Foot progression | 7.3 ± 7.1 | 7.5 ± 7.0 | −0.02, 0.418 | 9.6 ± 6.8 | 9.6 ± 6.9 | 0.01, 0.492 |

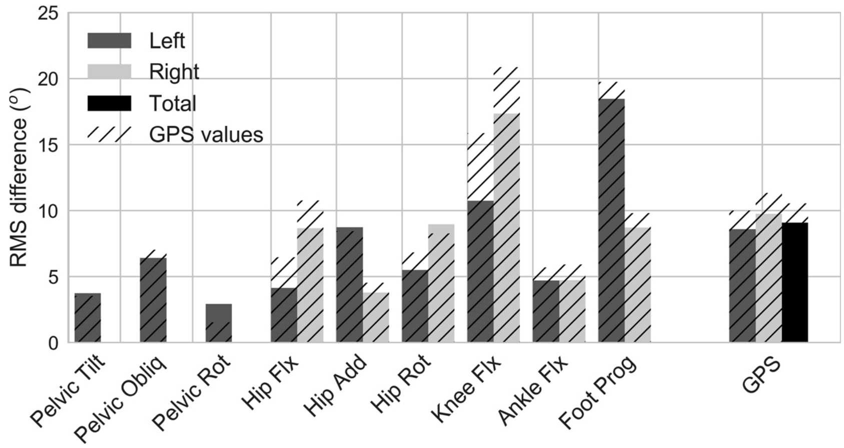


**Fig. 4.** The Movement Analysis Profile for the post-stroke participant with the greatest absolute difference between GPS and GPS$^v$ values (0.19 dimensionless speed). GPS$^v$ values for the left, right, and total scores are shown as dark grey bars, light grey bars, and black bars, respectively, and GPS values are presented as dashed bars.

might be differently affected by speed. In Fig. 3, the plot of the absolute difference between GPS and GPS$^v$ versus gait speed, the two subjects at speed ˜ 0.2 presented the largest deviations from the regression line and their distinct GPS and GPS$^v$ values are shown in Fig. 3 of the Supplementary material (third and fifth subjects at that plot). Note that for those two subjects, the alterations in their gait patterns were more affected by speed than for the other individuals because when the correction for speed was introduced, their GPS$^v$ dropped relatively more than for the other individuals. So, looking at both GPS and GPS$^v$ values, one can infer which individuals have their gait patterns more affected by speed; this information might be useful in the rehabilitation process.

There were limitations in this study that need to be acknowledged. Despite the advantages of the GPS compared with other gait indices, the application of other methods such as GDI and GGI were not considered in the present study. Additionally, as only older adults were analyzed, the results of the present study are applicable particularly to this age group. Moreover, due to the higher variability of the walking speed among our participants, it seems thus necessary to consider a larger sample size and to apply this new method to individuals with other disorders to conclusively demonstrate the usefulness of such method in the clinical context.

In conclusion, a modified version of the GPS, the Gait Profile Score velocity (GPS$^v$), is effective in reducing the impact of gait speed on GPS. However, the observed difference between the two methods was only around 1° for the slowest individuals in comparison to the reference dataset. Considering that the minimal clinically significant difference for the GPS is 1.6° [23], a discrepancy between GPS and GPS$^v$ of around 1° could be enough to alter the interpretation of an individual's gait pattern based solely on the GPS result.

## 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.2019.01.018.

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