

# Trunk Waist Gait Variable Description

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This is a summary of the variables that are used in the Shimmer gait algorithm which detect gait events for supervised, straight line walking with a Shimmer3 sensor mounted on the lower back.

	Variable	Unit
<b>Temporal Metrics</b>		
1	Steps	
2	stepTime_l	sec
3	stepTime_r	sec
4	stepTime	sec
5	stepTimeVar	
6	strideTime_l	sec
7	strideTime_r	sec
8	strideTime	sec
9	strideTimeVar	
10	strideTimeSD	
11	stepCadence	steps/min
12	strideCadence	strides/min
13	walkTime	sec
<b>Spatio-Temporal Metrics</b>		
14	meanGaitSpeed	m/sec
15	meanStepLength	m
16	meanStrideLength	m
<b>Symmetry Metrics</b>		
17	symmetryRatioStep	
18	symmetryRatioStride	
19	symmetryIndexStep	
20	symmetryIndexStride	
21	gaitAsymmetryStep	
22	gaitAsymmetryStride	
23	symmetryAngleStep	
24	symmetryAngleStride	
<b>Unbiased Auto-Correlation Metrics</b>		
25	Step_time_AP	sec
26	Stride_time_AP	sec
27	Step_time_VT	sec
28	Stride_time_VT	sec
29	Step_regularity_AP	
30	Step_regularity_ML	
31	Step_regularity_VT	
32	Stride_regularity_AP	
33	Stride_regularity_ML	
34	Stride_regularity_VT	
35	Asymmetry_AP	
36	Asymmetry_ML	

37	Asymmetry_VT	
38	APrms	
39	MLrms	
40	VTrms	
41	harmonic_ratio	

## Number of steps

The number of steps that were taken during the test are counted. This is based on the number of initial contact (IC) points found in the data. IC points are found based on the methods described in Zijlstra & Hof, 2003, which is seminal paper in the wearable sensor, gait analysis research space. In this paper, they show that IC locations are found on the anterior-posterior acceleration signal at the peak forward acceleration preceding the change of sign, as determined by the zero-crossing method. Many other researchers use the same feature in the anterior-posterior acceleration to identify initial contact [Godfey et al, 2015, Gonzalez et al, 2010, Hartmann et al, 2009, IJmker et al, 2011 & Senden et al, 2012]. Figure 1 shows the Zijlstra & Hof, 2003 method used to detect IC points on an anterior-posterior acceleration signal from the trunk.

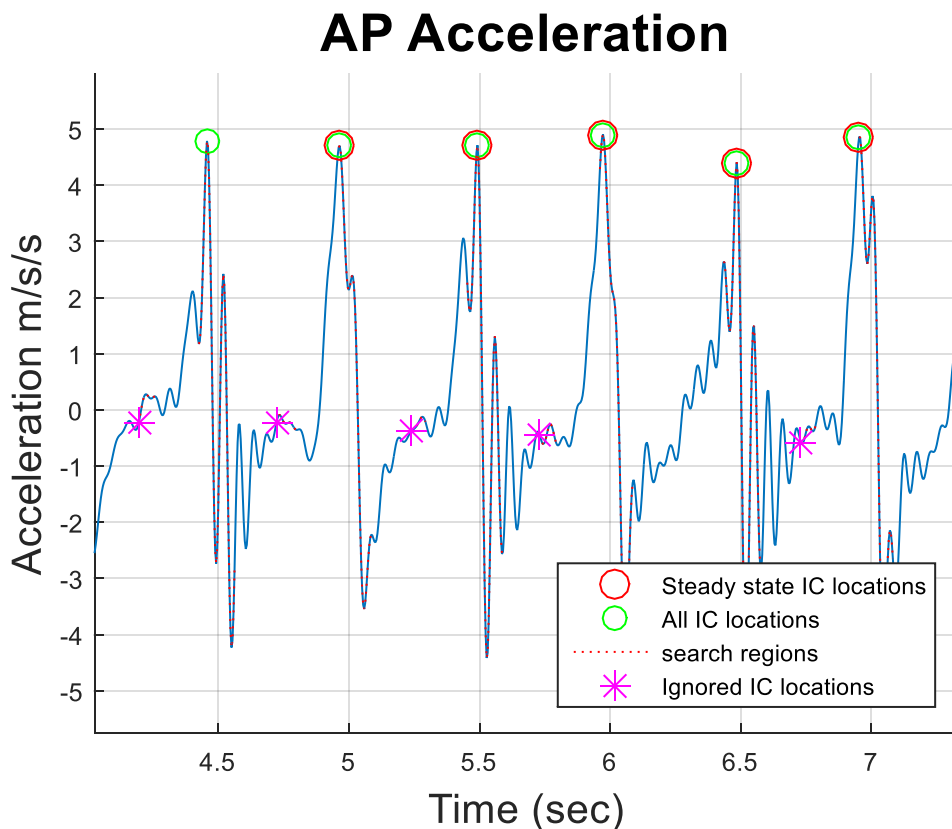


Figure 1 - IC locations are shown in red circles on the anterior-posterior acceleration signal. IC locations are found using the method proposed in Zijlstra & Hof, 2003.

Associated variables

- 1 - Steps

## Step time

Step time is defined as the amount of time from one initial contact to the next initial contact on the contra lateral leg. A step is identified as either left or right, by the foot that is swinging forward to touch down for the second initial contact; for example, a left step would be the time from a right foot initial contact until the next left foot initial contact. Step time can be shown for each step during the test, or it can be averaged over the whole test. Step times can also be displayed for left and right steps. Hollman et al, 2011 present normative step time information for healthy elderly individuals.

Associated variables

- 2 - stepTime\_l: average step time of all left steps
- 3 - stepTime\_r: average step time of all right steps
- 4 - stepTime: average step time of all steps
- 5 - stepTimeVar: variance of all step time measures during the test

## Stride time

Stride time is defined as the amount of time from an initial contact on one foot to the next initial contact on the same foot. It consists of two step times, left and right. Stride time can be shown for each stride during the test, it can be averaged over the whole test. Stride time can also be displayed for left and right strides.

Associated variables

- 6 - strideTime\_l: average stride time of all left strides
- 7 - strideTime\_r: average stride time of all right strides
- 8 - strideTime: average stride time of all strides

## Stride time standard deviation

The standard deviation of all of the stride times during the test. Hausdorff et al, 2001 showed that an elevated stride time variability, measured via standard deviation was predictive of future risk of falling in a group of 52 participants over the age of 70 years.

Associated variables

- 10 - strideTimeSD: Standard deviation of all the stride time measures

## Stride time variance

Coefficient of variation of all the stride times during the test. Previous work by Hausdorff et al, 2001 has suggested that the coefficient of variance and the standard deviation of stride time are highly correlated. Recent research has shown that dementia patients exhibit an increased stride time variability compared to an aged matched, healthy control group [IJmker et al, 2012].

Associated variables

- 9 - strideTimeVar: Variance of all the stride time measures

## Step cadence

This is calculated by dividing the number of steps by the walking time [Senden et al, 2012].

Associated variables

- 11 - stepCadence: Number of steps taken divided by total walking time

## Stride cadence

This is calculated by dividing the number of strides by the walking time.

Associated variables

- 12 - strideCadence: Number of strides taken divided by total walking time

## Walk time

The time in which it took the participant to complete the walking task.

Associated variables

- 13 - walkTime

## Mean gait speed

The walking distance divided by the walking time. Gait speed is measured in this manner commonly in the clinical setting; a recent clinical research review has suggested that the minimally clinically important difference in gait speed is from 0.10 to 0.20 m/s across multiple patient groups.

[Bohannon et al, 2014]. Studies which measure gait via a trunk mounted inertial sensor measure gait speed in the same manner [Senden et al, 2012, Hartmann et al, 2009, IJmker et al, 2012]. Bohannon et al, 1997 showed that maximum gait speed was a better predictor of age than comfortable gait speed.

Associated variables

- 14 - meanGaitSpeed

## Mean step length

This is calculated by dividing the number of steps taken during the test by the distance walked.

Previous work has obtained step length via this method and found a high discriminative power to classify elderly people according to the Tinetti scale [Senden et al, 2012].

Associated variables

- 15 - meanStepLength

## Mean stride length

This is calculated by dividing the number of strides during the test by the distance walked.

Associated variables

- 16 - meanStrideLength

## Symmetry metrics

Symmetry metrics are based on methods presented in Patterson et al, 2010. The authors present four of the most popular methods of assessing symmetry based on temporal gait metrics, but they suggest that it is only appropriate to select one and stick with it. In Cadence we provide all four symmetry metrics for both step and stride symmetry and leave it up to the user to select their desired method.

Based on the recommendations from Patterson et al, 2010, symmetry ratio is calculated with the larger step or stride time value at the numerator and the smaller value as the denominator. This

means that the symmetry ratio values are always over 1.0 and are easier to compare. Which side is the numerator is denoted via the sign in front of the symmetry ratio value. If the symmetry ratio is negative, then the right side had the longer step or stride time. If the symmetry ratio is positive, then the left side had the longer step or stride time. For equations 19 to 24 the right is considered to be the paretic value and the left is considered to be the non-paretic value.

$$17: \text{Step symmetry ratio} = \frac{\text{stepTime}_{\text{higher}}}{\text{stepTime}_{\text{lower}}}$$

$$18: \text{Stride symmetry ratio} = \frac{\text{strideTime}_{\text{higher}}}{\text{strideTime}_{\text{lower}}}$$

$$19: \text{Step symmetry index} = \left| \frac{(\text{stepTime}_{\text{paretic}} - \text{stepTime}_{\text{non-paretic}})}{0.5 (\text{stepTime}_{\text{paretic}} + \text{stepTime}_{\text{non-paretic}})} \right| \times 100\%$$

$$20: \text{Stride symmetry index} = \left| \frac{(\text{strideTime}_{\text{paretic}} - \text{strideTime}_{\text{non-paretic}})}{0.5 (\text{strideTime}_{\text{paretic}} + \text{strideTime}_{\text{non-paretic}})} \right| \times 100\%$$

$$21: \text{Step asymmetry} = \left| \left( 100 \times \left[ \ln \left( \frac{\text{stepTime}_{\text{partic}}}{\text{stepTime}_{\text{non-partic}}} \right) \right] \right) \right|$$

$$22: \text{Stride asymmetry} = \left| \left( 100 \times \left[ \ln \left( \frac{\text{strideTime}_{\text{partic}}}{\text{strideTime}_{\text{non-partic}}} \right) \right] \right) \right|$$

$$23: \text{Step symmetry angle} = \frac{\left| \left( 45^\circ - \arctan \left( \frac{\text{stepTime}_{\text{paretic}}}{\text{stepTime}_{\text{non-paretic}}} \right) \right) \times 100\% \right|}{90}$$

$$24: \text{Stride symmetry angle} = \frac{\left| \left( 45^\circ - \arctan \left( \frac{\text{strideTime}_{\text{paretic}}}{\text{strideTime}_{\text{non-paretic}}} \right) \right) \times 100\% \right|}{90}$$

## Unbiased Auto-correlation

Figure 1 shows a focused portion of the unbiased auto-correlation as calculated for the anterior-posterior acceleration. The auto-correlation of a signal is the direct mapping of the signal onto a time-shifted version of itself and the result summed over the length of the dataset. This procedure extracts all the common re-occurring features and is not dissimilar to the signals frequency spectrum. Figure 2 represents the autocorrelation  $f_c(t)$  of a signal where:

$$f_c(t) = \frac{1}{N - |t|} \sum_{i=1}^{N-|t|} x_i x_{i+t}$$

Alternatively, the *biased* autocorrelation would omit the “ $-|t|$ ” in the denominator of  $f_c(t)$ . The normalised autocorrelation coefficients ( $NFC(t)$ ) were then calculated as:

$$NFC(t) = \frac{f_c(t)}{f_c(0)} = \frac{\frac{1}{N - |t|} \sum_{i=1}^{N-|t|} x_i x_{i+t}}{\frac{1}{N} \sum_{i=1}^N x_i x_i}$$

The resulting  $NFC(t)$  is a double sided (symmetrical) spectrum of the signal from which key gait characteristics can be extracted.

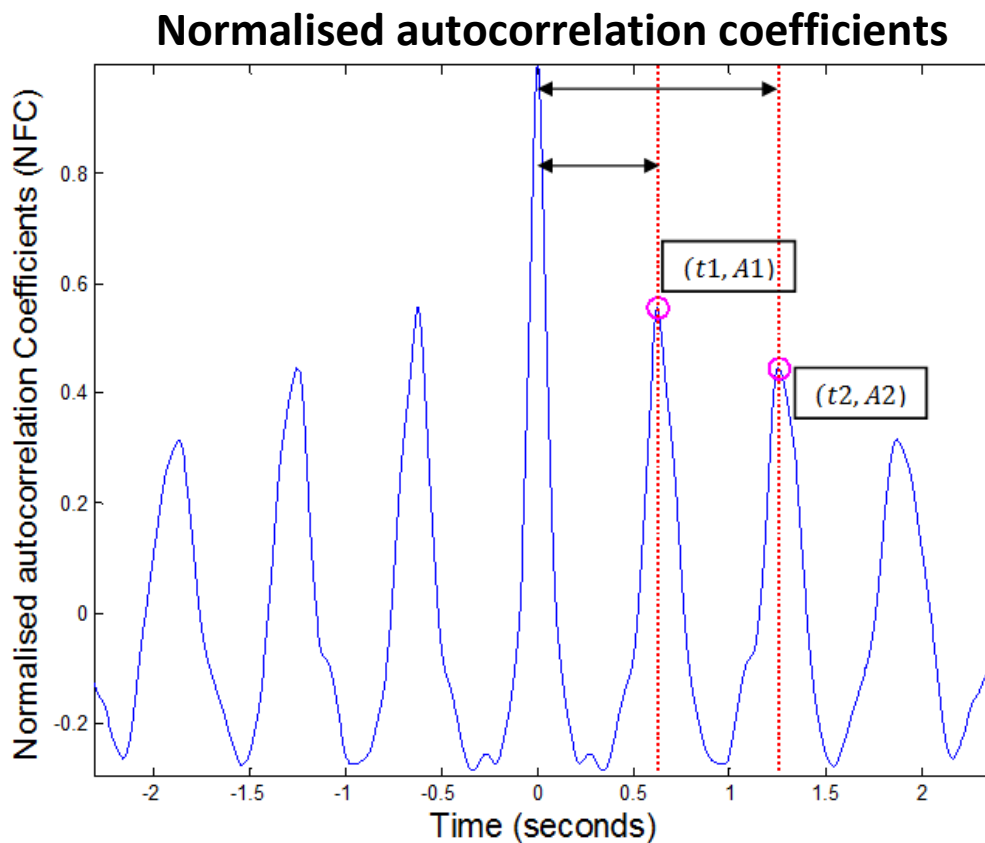


Figure 2 - Normalised unbiased autocorrelation coefficients

The use of an unbiased autocorrelation coefficient is used regularly when assessing gait via a trunk mounted inertial sensor [Kobsar et al, 2014, Saether et al, 2014, Yang et al, 2012].

Associated variables

- Step\_time\_AP
- Stride\_time\_AP
- Step\_time\_VT
- Stride\_time\_VT

## Step Regularity

Step regularity is shown in Figure 1 above as the point  $t_1, A_1$  located a phase shift of  $t_1$  seconds away from the central phase coefficient. The value of step regularity is the amplitude  $A_1$  and is taken as an expression of the regularity of the acceleration signal between neighbouring steps [1]. Typically, a low value of  $A_1$  might represent: (a) - irregular step times or (b) - a systematic asymmetry between left and right steps [Moe-Nilssen & Helbostad, 2004]. In (a), the expected value of  $A_2$  will also be low because this irregularity will also be true for strides in the gait sequence and, in the case of (b),  $A_2$ 's amplitude will be greater than  $A_1$  [Moe-Nilssen & Helbostad, 2004]. Note: the value of  $1/t_1$  gives the primary walking frequency.

Associated variables

- 29: Step\_regularity\_AP
- 30: Step\_regularity\_ML
- 31 - Step\_regularity\_VT

## Stride Regularity

Stride regularity is shown in Figure 1 above as the point  $t_2, A_2$  located a phase shift of  $t_2$  seconds away from the central phase coefficient. The value of stride regularity is the amplitude  $A_2$  and is taken as an expression of the regularity of the acceleration signal between neighbouring strides. Kobsar et al, 2014 showed differences in stride regularity between a healthy young and a healthy older population.

Associated variables

- 32: Stride\_regularity\_AP
- 33: Stride\_regularity\_ML
- 34 - Stride\_regularity\_VT

## Gait Symmetry

Gait Symmetry ( $D$ ) is directly computed from Step and Stride Regularity as:

$$D = |A_2 - A_1|$$

A smaller value of  $D$  can indicate a very symmetric gait while a small value of  $D$  would indicate an asymmetric gait style. Saether et al, 2014 found that a group of children with Cerebral Palsy had significantly higher levels of AP, ML and VT asymmetry when compared to healthy controls.

Associated variables

- 35: Asymmetry\_AP
- 36: Asymmetry\_ML
- 37: Asymmetry\_VT

## RMS of Acceleration

The RMS (Root-Mean-Square) of an Acceleration signal represents the mean strength of the signal and is the accepted method of determining the mean amplitude of any AC signal. RMS is calculated as

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2}$$

RMS is a very commonly discussed feature of an AC signal and is a key indicator of the power contained in a signal.

Associated variables

- 38: APrms
- 39: MLrms
- 40: VTrms



## Harmonic Ratio

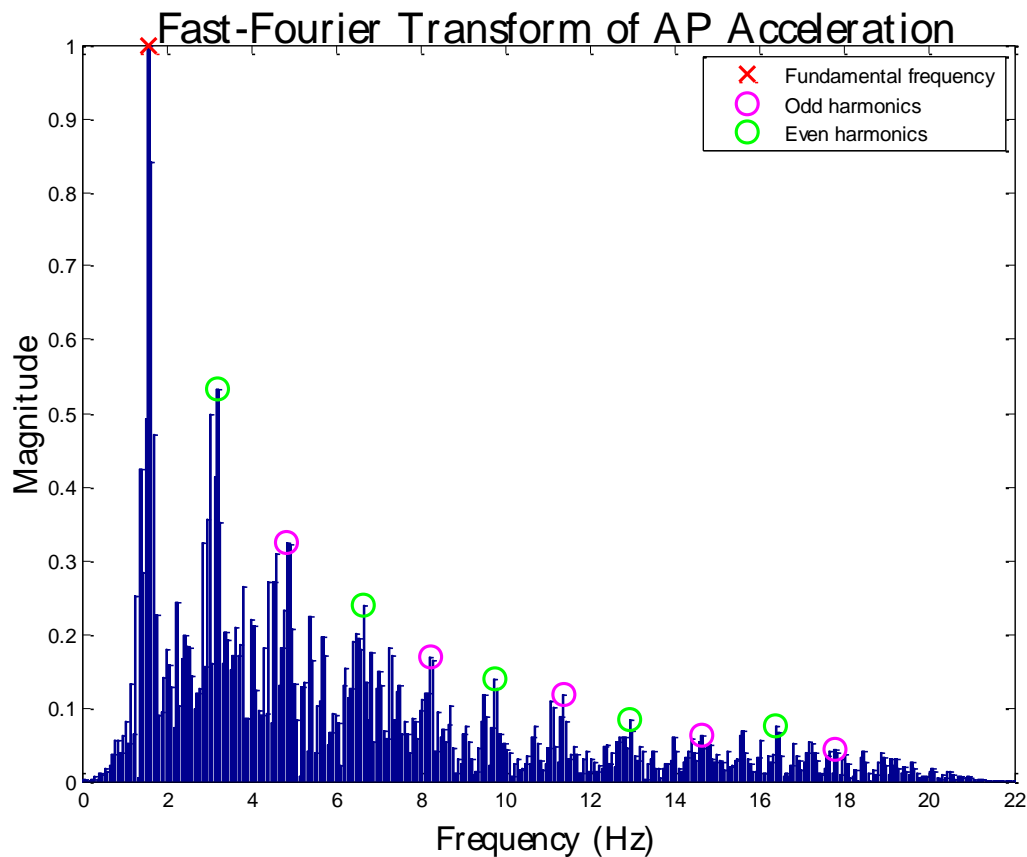


Figure 3: Fast Fourier Transform of AP Acceleration with markers on first 10 harmonics.

The Harmonic Ratio [Smidt et al, 1971] of a signal is calculated as:

$$\text{Harmonic Ratio} = \frac{\sum_1^5 \text{amplitude of even harmonic}}{\sum_1^5 \text{amplitude of odd harmonic}} \quad \{5\}$$

Menz et al, 2003 suggest taking the first ten even against the first ten odd harmonics in the ratio shown in Rosenstein et al, 1993. However, on inspection for our own data, it was decided that just using the first 5 odd harmonics v.s. the first 5 even harmonics would effectively yield the same result.

The Harmonic ratio is useful as it provides an indication of the smoothness and rhythm of acceleration patterns. The harmonic ratio is based on the premise that the unit of measurement from a continuous walking trial is a stride. A stable rhythmic gait pattern should therefore consist of acceleration patterns that repeat in multiples of two within any given stride, as these patterns are therefore 'completed' before taking subsequent strides. Acceleration patterns that do not repeat are problematic, as they produce out of phase accelerations that are not completed within each stride and therefore manifest as irregular accelerations during a walking trial [Menz et al, 2003]. The

harmonic ratio is a commonly used metric when using a trunk inertial sensor to obtain gait metrics [Ijmker et al, 2011 and Senden et al, 2012].

Associated variables

- 41: harmonic\_ratio

## References

Bohannon, Richard W., and Susan S. Glenney. "Minimal clinically important difference for change in comfortable gait speed of adults with pathology: a systematic review." *Journal of evaluation in clinical practice* 20.4 (2014): 295-300.

Godfrey, A., Del Din, S., Barry, G., Mathers, J. C., & Rochester, L. (2015). Instrumenting gait with an accelerometer: a system and algorithm examination. *Medical engineering & physics*, 37(4), 400-407.

González, Rafael C., Antonio M. López, Javier Rodríguez-Uría, Diego Álvarez, and Juan C. Alvarez. "Real-time gait event detection for normal subjects from lower trunk accelerations." *Gait & posture* 31, no. 3 (2010): 322-325.

Hausdorff, Jeffrey M., Dean A. Rios, and Helen K. Edelberg. "Gait variability and fall risk in community-living older adults: a 1-year prospective study." *Archives of physical medicine and rehabilitation* 82.8 (2001): 1050-1056.

Hartmann, Antonia, et al. "Reproducibility of spatio-temporal gait parameters under different conditions in older adults using a trunk tri-axial accelerometer system." *Gait & posture* 30.3 (2009): 351-355.

Hollman, John H., Eric M. McDade, and Ronald C. Petersen. "Normative spatiotemporal gait parameters in older adults." *Gait & posture* 34, no. 1 (2011): 111-118.

Ijmker, Trienke, and Claudine JC Lamoth. "Gait and cognition: the relationship between gait stability and variability with executive function in persons with and without dementia." *Gait & posture* 35.1 (2012): 126-130.

Kobsar, Dylan, Chad Olson, Raman Paranjape, Thomas Hadjistavropoulos, and John M. Barden. "Evaluation of age-related differences in the stride-to-stride fluctuations, regularity and symmetry of gait using a waist-mounted tri-axial accelerometer." *Gait & posture* 39, no. 1 (2014): 553-557.

Menz et al. "Acceleration patterns of the head and pelvis when walking on level and irregular surfaces". *Gait & Posture* 2003; Volume18, Issue 1; 35:46.

Moe-Nilssen, L. Helbostad. "Estimation of gait cycle characteristics by trunk accelerometry." *J. Biomechanics* 2004; 121:126.

Patterson, Kara K., et al. "Evaluation of gait symmetry after stroke: a comparison of current methods and recommendations for standardization." *Gait & posture* 31.2 (2010): 241-246.

Rosenstein MT, Collins JJ, De Luca CJ. "A practical method for calculating largest Lyapunov exponents from small data sets". *Phys D* 1993;65:117-34.

Saether, Rannei, Jorunn L. Helbostad, Lars Adde, Siri Brændvik, Stian Lydersen, and Torstein Vik. "Gait characteristics in children and adolescents with cerebral palsy assessed with a trunk-worn accelerometer." *Research in developmental disabilities* 35, no. 7 (2014): 1773-1781.

Senden, R., et al. "Accelerometry-based gait analysis, an additional objective approach to screen subjects at risk for falling." *Gait & posture* 36.2 (2012): 296-300.

Smidt GL, Arora JS, Johnston RC. "Accelerographic analysis of several types of walking" . *Am J Phys Med* 1971;50:285\_ 300.

Yang, Mingjing, Huiru Zheng, Haiying Wang, Sally McClean, and Dave Newell. "iGAIT: an interactive accelerometer based gait analysis system." *Computer methods and programs in biomedicine* 108, no. 2 (2012): 715-723.

Zijlstra, Wiebren, and At L. Hof. "Assessment of spatio-temporal gait parameters from trunk accelerations during human walking." *Gait & posture* 18.2 (2003): 1-10.