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Estimation of gait cycle characteristics by trunk accelerometry

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Abstract

This study reports on the novel use of a portable system to measure gait cycle parameters. Measurements were made by a triaxial accelerometer over the lower trunk during timed walking over a range of self-administered speeds. Signals from each trial were transformed to a horizontal–vertical coordinate system and analyzed by an unbiased autocorrelation procedure to obtain cadence, step length, and measures of gait regularity and symmetry. By curvilinear interpolation, speed-dependent gait parameters could be compared at a normalized speed. It was demonstrated that analysis of gait cycle parameters which previously required fixed laboratory equipment and paced walking procedures, now can be made from data obtained by a timing device and a portable sensor at free walking speeds.

Keywords: Human; Gait kinematics; Accelerometry; Autocorrelation; Ambulatory measurements

1. Introduction

A large number of reports have been presented on the significance of gait parameters to diagnose impairments in balance control, assess functional ability, and predict risk of falling. Such parameters include cadence, step length and walking speed, which can be measured without the need of fixed laboratory equipment. By use of instrumented walkways more detailed records of temporal and spatial parameters may be obtained.

Variables reported typically change with walking speed, however (Winter, 1991), and differences in walking speed may therefore confound the results. This poses an important restriction on the interpretation of such data. Still, a common procedure is to have subjects walk at a self-selected preferred speed without controlling for differences in speed between sessions or subjects (Winter et al., 1990; Lord et al., 1996; Wolfson et al., 1985; Hallett et al., 1993). Some investigators therefore administer paced walking, where either walking speed is controlled as on a treadmill (Crane and Demer, 2000) or cadence is standardized by a metronome (Krebs et al., 2002). However, such constraints may affect walking behavior and thus restrict the validity of the results.

Most commonly, the average outcome over a given walking distance is reported, but variability between steps or strides may give additional information. Measures like within-subject step-length variability and within-subject step-width variability, however, require costly equipment like an instrumented walkway (Grabiner et al., 2001) or cumbersome analysis of ink marks (Sekiya et al., 1997; Helbostad and Moe-Nilssen, 2003), which have restricted their use in field research.

In recent years, low inertia piezoresistant accelerometers have become widespread at low cost, and accelerometry has been described for various biomechanical purposes (Aminian et al., 1999b; Nigg, 1994; Yack and Berger, 1993). Still, however, accelerometry is not in common use for gait analysis, possibly because unwanted variability caused by the gravity factor was not adequately dealt with in the past. Procedures have now been described to eliminate the gravity component (Moe-Nilssen, 1998a), and to assess trunk accelerations in walking (Moe-Nilssen, 1998b) and standing (Browne and O'Hare, 2001) as measures of balance control. The operational simplicity and high capacity of present day accelerometric technology suggest a method suitable for use in settings not restricted to a laboratory.

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Several authors have attempted to derive common gait cycle parameters from accelerometry data. Thus Evans et al. (1991) used a uniaxial accelerometer to identify each heel strike. Auvinet et al. (1999) applied a biaxial accelerometry unit to derive measures of cycle frequency, stride symmetry, and stride regularity at preferred walking speed, while Aminian et al. (1999a) measured temporal parameters using two accelerometers, also at preferred speed. None of these investigators, however, reported how their chosen outcome measures might be affected by changes in preferred walking speed between sessions and subjects. This source of variability may camouflage relations among other variables of interest.

It is a research issue to develop procedures utilizing the advantages of ambulatory technology, at the same time eliminating unwanted variability associated with self-administered walking speeds. In this paper, we suggest a protocol for estimation of well-known parameters like cadence, step length, and measures of gait regularity and symmetry from data obtained by a single triaxial accelerometer, also describing procedures to control for the confounding effect of differing gait speed, when subjects are walking at self-administered speeds.

2. Methods

2.1. Instrumentation and data acquisition

Linear acceleration was measured along three orthogonal axes using a low-inertia (15 g) triaxial piezoresistant accelerometer snugly secured to the test subjects by a fixation belt over the L3 region of the spine. The accelerometer was connected to a battery-operated portable PCMCIA data logger also worn by the subject. Analog signals were low-pass filtered at 55 Hz before being sampled at 128 Hz. The digitized signals were stored on interchangeable 20 Mb PCMCIA cards, and subsequently transferred to a computer for off-line processing. Whenever a sensing axis deviates from the horizontal plane, a piezoresistant accelerometer measures gravity as well as dynamic acceleration. An accelerometer positioned over the lower part of the back may be tilted due to the curvature of the back, the postural alignment of the walking subject and inaccuracy in positioning of the instrument. Correction must therefore be made for the static gravity component in order to assess true dynamic acceleration. When a person is walking at an even speed, the best estimate of mean dynamic acceleration along any axis is nil. Measured mean acceleration away from nil is assumed to be caused by the mean static gravity component along that axis. Thus the average tilt of the measuring axes during each walking trial can be calculated, and data transformed to a horizontal–vertical coordinate system by a trigonometric algorithm. Details and mathematics of this procedure are described elsewhere (Moe-Nilssen, 1998a). Precision, accuracy, and reliability on a test–retest basis have been demonstrated with good results (Moe-Nilssen, 1998a; Moe-Nilssen, 1998c).

2.2. Test procedure

Subjects are instructed to walk repeatedly back and forth a straight walkway at different self-administered speeds from very slow to very fast in order to obtain data over a range of walking speeds representative for that subject. Walking time over a measured distance disregarding at least 1.5 m at each end of the walkway is registered by photocells synchronized with the accelerometry device. Timed walking distance is typically 6–9 m depending on the population to be tested and availability of space. Number of trials per subject may vary, depending on the capacity of the population to be tested. See previous reports for details on test environments and instructions to subjects (Moe-Nilssen, 1998c; Moe-Nilssen et al., 1999).

2.3. Autocorrelation procedure

A raw autocorrelation coefficient (A) is the sum of the products of a time series x_i ($i = 1, 2, \ldots, N$) multiplied by a time-lagged replication of the time series (x_{i+m}), where the lag parameter m is the phase shift in number of samples:

$$A = \sum_{i=1}^{N-|m|} x_i x_{i+m}. \tag{1}$$

An estimate of an autocorrelation function is represented by a sequence of autocorrelation coefficients over increasing time lags. A cyclic signal will produce autocorrelation coefficients with peak values for lags equivalent to the periodicity of the signal, here called dominant periods. Plots of an autocorrelation estimate can thus be used to inspect the structure of a cyclic component within a time series. Since phase shifts can be performed with identical results in both positive and negative direction relative to the original time series, an autocorrelation plot is conventionally organized symmetrically with the zeroth shift located centrally. For a time series of trunk accelerations during walking, autocorrelation coefficients can thus be produced to quantify the peak values at the first and second dominant period, representing phase shifts equal to one step and one stride, respectively.

Either biased or unbiased estimates of the autocorrelation coefficient can be computed. The biased estimate is produced by dividing the raw autocorrelation coefficient in Eq. (1) by the number of samples in the time series to be analyzed:

$$A_{\text{biased}} = \frac{1}{N}\sum_{i=1}^{N-|m|} x_i x_{i+m}. \tag{2}$$

The unbiased alternative is produced by dividing the raw autocorrelation coefficient by the number of samples representing the overlapping part of the time series and the time-lagged replication:

$$A_{\text{unbiased}} = \frac{1}{N-|m|}\sum_{i=1}^{N-|m|} x_i x_{i+m}. \tag{3}$$

The choice of estimate is not trivial. The denominator N in Eq. (2) represents the number of samples in the time series to be analyzed, and is independent of the number of terms ($N-|m|$) in the nominator. Therefore, with increasing values of the lag parameter m, the number of terms in the nominator will decrease and the amplitudes of A_{biased} will attenuate. This is not the case for the unbiased estimate in Eq. (3) where the number of terms in the nominator ($N-|m|$) is always equal to the value of the denominator which is also ($N-|m|$). For N large and m small with respect to N, the values obtained by using Eq. (3) differ very little from those obtained by use of Eq. (2), but for sequences representing a limited number of cycles, the attenuation from one dominant period to the next is noticeable (Bendat and Piersol, 1971). The two alternative estimates are illustrated in Fig. 1 for vertical trunk acceleration during normal walking. The biased alternative demonstrates faithful periodicity, but a tapering of the amplitudes towards the tails, while the unbiased alternative produces autocorrelation coefficients with no obvious attenuation until the curve deteriorates at the tails.

Matlab Signal Processing Toolbox 6.0 (The MathWorks Inc., Natick, MA) was used in the computation of the autocorrelation coefficients. Matlab offers two alternative algorithms for computing unbiased autocorrelation estimates, the ⟨xcorr⟩ function and the ⟨xcov⟩ function, where ⟨xcov⟩ subtracts the mean of its inputs, and then calls ⟨xcorr⟩. Since the ⟨xcov⟩ algorithm removes any offset, this is mathematically a sound algorithm to use, before normalizing the coefficients to 1.0 at zero lag.

2.4. Estimation of cadence and step length

Cadence, defined as steps per minute, can be computed from the vertical or anteroposterior axis of a sequence of trunk accelerations when walking distance and walking time is known, as well as sampling frequency and samples per dominant period of the autocorrelation function. Let D be the distance (in meters) to be included in analysis, S the time (in seconds) to walk D meters, f the sampling frequency (Hz), n the samples per dominant period, N the samples per D meters, M the number of steps per D meters, and c the cadence (steps per minute).

When D, S, f, and n are known, the remaining parameters can be derived: $N = Sf$, $M = N/n$, $c = 60M/S$. By substitution cadence can be expressed

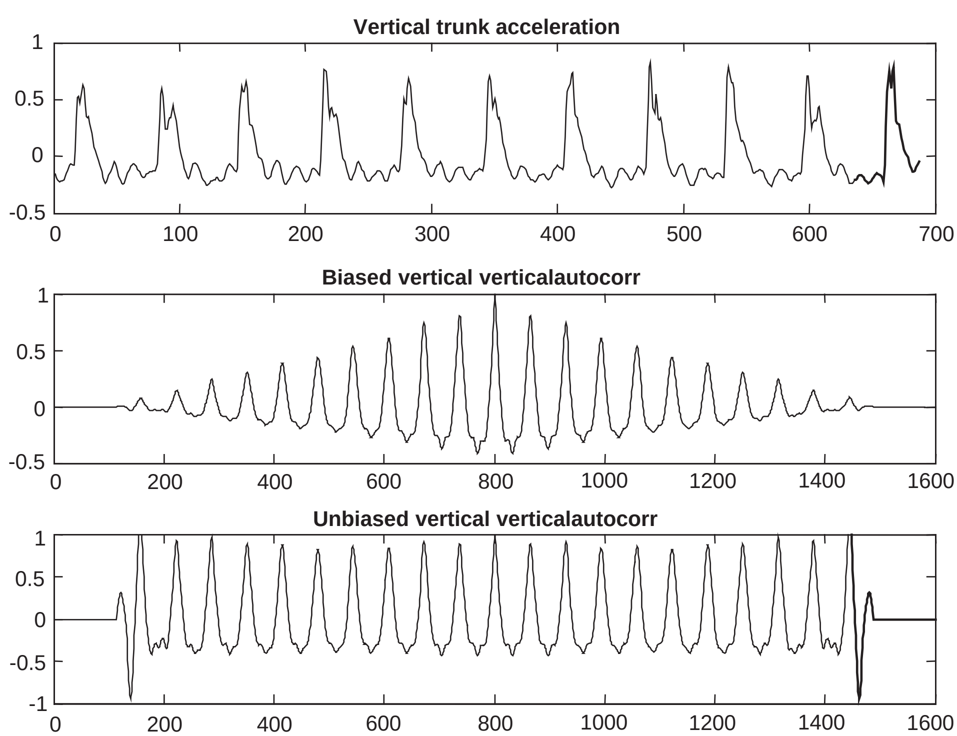

Fig. 1. Vertical trunk acceleration curve (top), biased (middle) and unbiased (bottom) autocorrelation plots of normal gait.

as a function of f and n:

$$c = 60(N/n)/(N/f) = 60f/n. \tag{4}$$

Since n when derived from an autocorrelation function is always an integer, the resolution of c is restricted to the quantization step size which is the difference between two successive values of c (Proakis and Manolakis, 1992). An estimate of the quantization step size $\Delta(c_n)$ can thus be calculated as the difference between c_n and its neighboring value c_{n+1}:

$$\Delta(c_n) = (c_n - c_{n+1}). \tag{5}$$

By substitution of Eq. (4) in Eq. (5), $\Delta(c_n)$ can be expressed as

$$\Delta(c_n) = 60f/n - 60f/(n+1) = 60f/(n^2+n). \tag{6}$$

For instance, 80 samples per dominant period and a sampling frequency of 128 Hz returns a cadence of 96, and a resolution of 1.2 steps/min. This is equivalent to 0.12 steps for a walking distance of 6 m and walking speed 1 m/s.

As a convenient corollary, mean step length (l) over the test sequence can be computed as: $l = D/M = vn/f$ where v is walking speed in m/s. On the same grounds as demonstrated for the resolution of c, the resolution of l is restricted to the quantization step size $\Delta(l_n)$ which can be computed as

$$\Delta(l_n) = (l_{n+1} - l_n) = v(n+1)/f - vn/f = v/f. \tag{7}$$

Thus, values from the example above return a resolution of mean step length of <0.008 m.

2.5. Estimation of gait regularity and symmetry

Fig. 2 shows the middle section of an unbiased and normalized autocorrelation sequence of vertical trunk acceleration during normal walking. Since the first dominant period represents a phase shift of one step ($d1$), the autocorrelation coefficient at the first dominant period A_{d1} is an expression of the regularity of the acceleration signal between neighboring steps. There are two obvious reasons for a low A_{d1}; one is a generally low regularity between steps, the other a systematic asymmetry between left and right steps (a step being the period from one footfall to the next contralateral footfall). In the first case, the vertical autocorrelation coefficient at the second dominant period A_{d2} will remain low because there is also low regularity between strides (a stride being the period from one footfall to the next ipsilateral footfall). In the second case, A_{d2} will tend to be higher than A_{d1}. Thus, for the vertical axis closeness of each of A_{d1} and A_{d2} to 1.0 reflects step and stride regularity, respectively, while closeness of A_{d1}/A_{d2} to 1.0 reflects symmetry. Fig. 3 is an example of asymmetric gait showing the autocorrelation sequences of the vertical and mediolateral axes. For the mediolateral axis $A_{d1} \approx -1.0$ and $A_{d2} \approx 1.0$ will represent step and stride regularity. Regularity and symmetry coefficients derived from Figs. 2 and 3 are shown in Table 1.

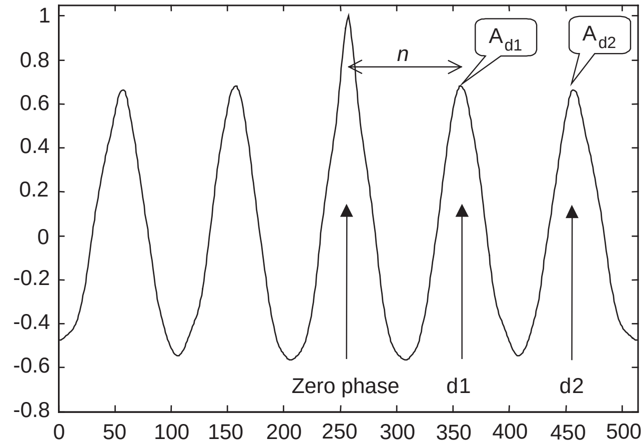

Fig. 2. Central part of unbiased autocorrelation coefficient sequence from a vertical axis trunk accelerometry time series during walking, including two dominant periods (one stride). Output has a length of 513 samples, with zero phase at sample 257. $d1$ = phase lag equivalent to one step; $d2$ = phase lag equivalent to one stride; A_{d1} = autocorrelation coefficient for neighboring steps; A_{d2} = autocorrelation coefficient for neighboring strides; n = samples per step.

2.6. Controlling for walking speed

When data are obtained from repeated trials representing different walking speeds, a curve estimate can be calculated over a range of speeds for each gait parameter. From the curve estimate, a point estimate at a standardized speed can be chosen as test parameter. Thus, test parameters can be compared at a common walking speed, even if subjects walk at self-administered speeds, which may vary between sessions and between subjects.

Since the relation between a gait variable and walking speed may not be linear, a curvilinear curve estimate may be appropriate. In Fig. 4 the relation between cadence and walking speed is used as an example. Cadence was plotted against gait speed for two subjects, with quadratic curve estimates based upon data from 8 trials representing different self-administered walking speeds. Point estimates were calculated at 1.0 m/s. Here the subject who demonstrated highest cadence at preferred speed, is represented by the lower of the two curves, and therefore also by lowest cadence at any normalized speed.

3. Discussion

We have demonstrated how gait cycle periodicity of trunk acceleration data can be analyzed by unbiased

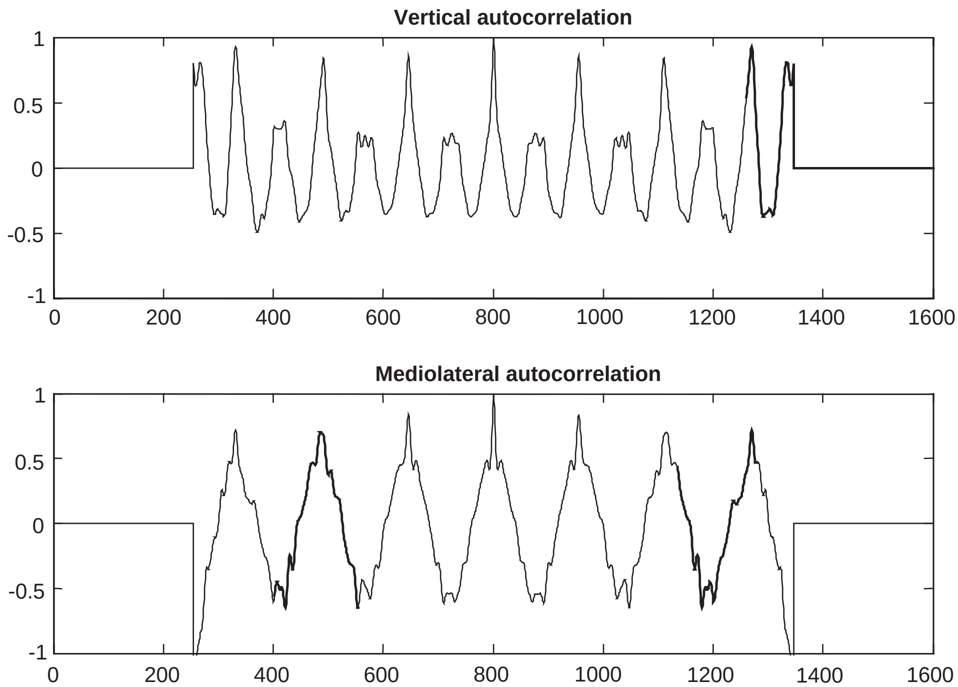

Fig. 3. Vertical and mediolateral autocorrelation plots of hemiplegic gait from a subject with sequela from a cerebral insult 9 years previously.

Table 1
Gait regularity and symmetry coefficients in two subjects with normal and asymmetric gait

		Normal gait[a]	Asymmetric gait[b]
Vertical	Step regularity (A_{d1})	0.89	0.26
	Stride regularity (A_{d2})	0.91	0.86
	Step symmetry (A_{d1}/A_{d2})	0.98	0.31
Mediolateral	Step regularity (A_{d1})	−0.85	−0.55
	Stride regularity (A_{d2})	0.85	0.84
	Step symmetry (A_{d1}/A_{d2})	−1.00	−0.65

A_{d1}, autocorrelation coefficient at first dominant period.
A_{d2}, autocorrelation coefficient at second dominant period.
[a] See Fig. 2.
[b] See Fig. 3.

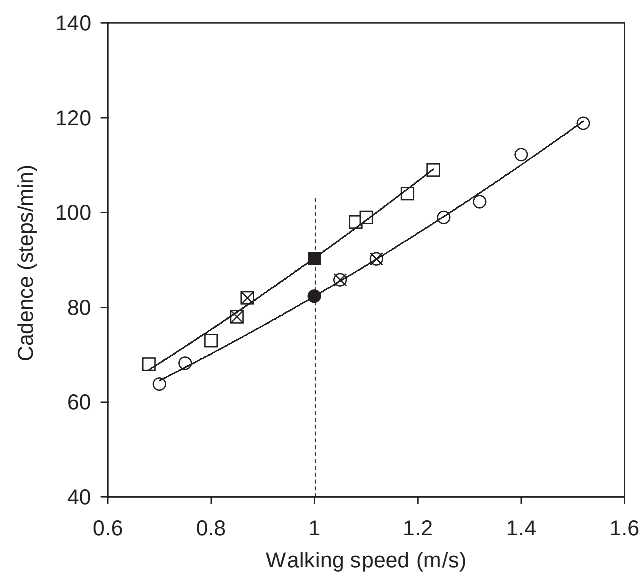

Fig. 4. Cadence versus gait speed (white bullets) with quadratic curve estimates (solid lines) and point estimates at 1.0 m/s (black bullets) for two subjects, each based upon data from eight trials representing different self-administered walking speeds. Bullets marked x indicate trials at preferred speed.

autocorrelation procedures to give cadence, step length and measures of gait regularity and symmetry. Further we have suggested procedures to control for variability introduced by differences in walking speed, still allowing subjects to walk at self-administered speeds. Reliability and validity of the derived parameters are issues for ongoing research.

The idea of analyzing gait data by autocorrelation is not new (Barrey et al., 1994; Auvinet et al., 1999), but as shown in our report, a biased alternative is not well suited for comparing autocorrelation coefficients representing different time lags. To our knowledge, unbiased autocorrelation procedures have never been suggested for gait cycle analysis.

Variability demonstrated during a single walking sequence may not be representative if the data sequence is of limited length. Thus Auvinet et al. (1999) recommended a walking distance of 40 m to optimize reliability. While a long walking distance may reduce attenuation of a biased autocorrelation curve, variability in walking speed during the trial may cause additional measurement error. We therefore chose a different strategy, avoiding the attenuation problem by utilizing an unbiased autocorrelation function, and minimizing random variability in data by a curve estimation procedure including data from several sequences representing a range of walking speeds. The final procedure of calculating a point estimate at a normalized speed controlled for the confounding effect of differing walking speeds between trials and subjects.

A limitation of the unbiased autocorrelation estimate is an increase in variance for large values of the lag parameter m in Eq. (3), especially as m approaches N. This is due to the fact that fewer data points enter into the estimate for large lags (Proakis and Manolakis, 1992). We only apply lags corresponding to one and two steps from a total of ten steps or more, however, thus minimizing the estimation error.

We have not yet investigated to what degree measures of gait regularity and symmetry are associated with walking speed, and previous reports are inconsistent. Thus Sekiya et al. (1997) found step-length variability to be smaller at preferred speed compared to slow and fast speeds in healthy students, while step-width variability increased with increasing speed. It should be noted that the regularity and symmetry measures suggested in this report, as well as similar measures suggested by Auvinet et al. (1999) are not directly comparable to measures based upon footfall identification, since autocorrelation coefficients include information also about the process between footfalls. More research is needed to enlarge upon these aspects.

One may question the rationale for using technically advanced methodology to estimate cadence and step length, when observation of heel strike and a stopwatch might suffice. It is an advantage of the methodology described in this report, however, that also other gait measures are obtained from the same series of raw data, including preferred and fast walking speeds, trunk accelerations, gait regularity and symmetry. When unbiased autocorrelation analysis is used, and speed dependent data are normalized for walking speed, we believe that important concerns with respect to validity have been taken away.

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