Validity of Four Gait Models to Estimate Walked Distance From Vertical COG Acceleration

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Pedometers are basically step counters usually used to estimate the distance walked by a pedestrian. Although their precision to compute the number of steps is quite accurate (about 1%), their feasibility to estimate the walked distance is very poor, as they do not consider the intrinsic variability of human gait. Reported results show values of 10% of precision in optimal conditions, increasing to 50% when conditions differ. Electronic accelerometer-based pedometers base their functioning on a basic processing of the vertical acceleration of the waist. Recently, different approaches have been proposed to relate such signals to the step length. This can lead to an improvement of the performance of this kind of device for estimating the walked distance. In this article, we analyze four gait models applied to the vertical accelerations of the body’s center of gravity, three biomechanical and one empirical. We compare their precision and accuracy. Results support the superior performance of three of them over an ideal pedometer. We also analyze their feasibility to be implemented in pedometer-like devices.

Keywords: biomechanics, kinematics, step length, gait events, accelerometry, pedometer

Electronic pedometers are low-cost devices that can be used to measure the distance walked by a pedestrian by combining step detection and counting with step length estimation. Various studies have been conducted to evaluate and compare the performance of popular brands of commercial devices. These studies are primarily centered on the accuracy of the step detection and counting capabilities in both laboratory and free living conditions (Bassett et al., 1996; Crouter et al., 2003; Schneider et al., 2003; Schneider et al., 2004; Le Masurier & Tudor-Locke, 2003; Le Masurier et al., 2004). False detections during nonwalking conditions have been addressed by evaluating the pedometer during motor vehicle travel on paved roads (Le Masurier & Tudor-Locke, 2003). Performance on the elderly and obese populations has also been studied (Melanson et al., 2004). Global conclusions are that pedometers are in general highly accurate for assessing steps. Mean values of ±1% of actual steps have been reported for a wide class of devices. This accuracy degrades only at very slow walking speeds. On the other hand, only a few studies address the capabilities of pedometers for estimating the walked distance (Bassett et al., 1996; Crouter et al., 2003). Reported results show a mean estimation of ±10% of actual distance in optimal conditions of application. This accuracy easily degrades when tested under conditions different from those under which the pedometer was tuned, reaching values of up to 50% of error (Crouter et al., 2003). Explanation for this poor performance is straightforward. Commercial pedometers use a fixed user-provided value for step-length estimation. Needless to say, it does not reflect the complex nature of step variability in human walking (Danion et al., 2003; Hausdorff, 2005).

Pedometers are typically worn on the belt and react to the movement of the waist during gait cycles. As a consequence, a wide range of pedometers are based on an accelerometer-type device. Nevertheless, the processing of the measured acceleration is trivial and usually restricted to the analysis of zero crossings for step counting (Crouter et al., 2003; Schneider et al., 2004).

With the recent advent of accelerometry technology at reduced prices and sizes (micro-electromechanical systems, or MEMS), a great deal of work has been done on the estimation of step length from the acceleration of different regions of the body, with particular attention to points on (or close to) the waist. Great attention has been paid to the proposal of Zijlstra (Zijlstra & Hof, 1997), which describes a biomechanical model relating step length to the vertical acceleration of the body’s center of gravity (COG) by means of an inverted pendulum model. This model has been recently extended, claiming that a better performance is achieved (González et al., 2007). Accelerometer manufacturers propose also, as technical notes, general descriptions that relate the acceleration of
the waist to step length. The main purpose is to encourage the development of applications of their technology that can attract potential customers. Among them, we have focused our attention on one that relates the vertical acceleration range of the hip with step length (Weinberg, 2002) and another that relates step length with the angular velocity of the hip (VTI, 2006).

These approaches offer a feasible alternative to improve the performance of accelerometer-based pedometers when used for walked distance estimation. In this article, we analyze and compare their precision and accuracy. We restrict our analysis to simplified conditions, addressing stable walking, where a set of users walk along a flat straight path of about 20 m in length. We will also address a qualitative comparison regarding their suitability (mainly through the analysis of their computational requirements) for the implementation of commercial devices, thus giving a glimpse of their expected impact on the actual state of technology of low-cost devices for walked distance estimation from body-fixed sensors.

Methods

A sample of 9 men and 7 women were included in this study, with ages ranging from 21 to 44 years and height from 158 cm to 186 cm. Weight was not registered because several subjects objected to giving such information. Nevertheless, visual inspection showed a usual population of nonobese individuals. All subjects appeared to be free of any impairment of the locomotion system that could affect the experiments. No footwear requirements were made for the experiments. All subjects gave their informed consent for their data to be used for the analyses.

Anthropometric parameters were manually measured in the preliminaries of the experiments. Leg length was measured from the floor to the accelerometer position (L1) and from the external malleolus to the trochanter major (L2), as requested by the different methods. L1 ranged from 86.0 to 102.0 cm (91.29 ± 5.3), and L2 ranged from 72.0 to 92.0 cm (81.6 ± 5.3). Foot lengths were measured as the length of the insole of the shoes, and ranged from 24.0 to 30.0 cm (26.5 ± 2.1).

Subjects were instructed to walk 12 independent excursions along a 25-m long path in a straight flat interior corridor. We decided to remove the initial and final 2.5 m of each excursion because gait is not stable during starting and stopping segments. For such purpose, floor marks were placed with a gap of 1 cm at the beginning and end of the 20-m central segment. Two camcorders were placed to record the position of the feet in those areas. Traveled distance was measured as the distance between the initial contact (IC) event, visually identified in each camcorder, with a maximum error of ±1 cm. A panoramic camcorder was used to record the general conditions of the experiments. Camcorders and acceleration signals were time-synchronized by inserting a special mark in both systems. Synchronization error was about 0.03 s.

Walking velocities were freely chosen, with the single condition of walking four excursions at slow, four at preferred, and four at fast velocities. Users were advised to maintain a constant velocity in each excursion. Subjects were allowed to turn freely between each excursion, and to walk freely or to rest between tests.

Raw acceleration data were gathered by means of an Xsens MTx accelerometer fixed close to the L3 vertebral position, accepted as a fine approximation of the COG during normal walking (Auvinet et al., 2002). The device was fixed to the lower lumbar spine by means of an adjustable corset to avoid movement artifacts. The axes of the accelerometer were approximately aligned with the anatomical axes.

Measurement range was 2 g, with g being the gravity acceleration. Data were gathered at 100 Hz, using 12-bit A/D conversion. The MTx sensor is wired to an Xsens Xbus Master, placed on the subject’s belt. All data were stored in a PC by means of a Bluetooth communications link.

Four models were tested: Zijlstra, SiMuR, VTI, and Quarter Root. Zijlstra (M1) is based on the inverted pendulum model (Figure 1, left). The antero-posterior displacement (d) can be related to vertical displacement (h), according to the equation

$$d = 2\sqrt{2L_1h - h^2}$$

(Zijlstra & Hof, 1997), where \(L_1\) is the leg length measured from the floor to the accelerometer. The requirements are having (1) the subject’s leg length, measured from the floor to the accelerometer position, and (2) IC events detection. The procedure is as follows:

i. Vertical acceleration is low-pass filtered (20 Hz) by a fourth-order zero lag Butterworth filter.
ii. Vertical position of COG is computed as the double integral of the acceleration.
iii. Vertical position is high-pass filtered (0.1 Hz) by a fourth-order zero lag Butterworth filter to remove the signal drift.
iv. Steps are segmented using IC time events.

For each step: (v-a) the vertical excursion is computed as the difference between the maximum and the minimum of COG position and (v-b) the antero-posterior displacement is computed from the formula using the vertical excursion and corrected with a constant factor (\(k = 1.25\)).

The SiMuR (M2) is based on a modified pendulum model (Figure 1, center). The step cycle is divided into two phases: double stance (from IC to contralateral final contact [FC]) and single stance (from contralateral FC to next IC). The inverted pendulum model is a good approach only during single stance. During double stance, displacement is constant and related to the foot size (González et al., 2007). The requirements are (1) subject’s leg length measured from the external malleolus to trochanter major (\(L_1\)), (2) subject’s foot length (\(F\)), (3)
IC events detection, and (4) FC events detection. The procedure is as follows:

i. Steps are segmented using IC events.

ii. For each step: (ii-a) The mean value of the vertical acceleration is eliminated; (ii-b) an initial approximation is obtained of the instantaneous vertical velocity integrating the acceleration obtained in the previous step; (ii-c) vertical velocity is obtained by eliminating the mean value of the velocity calculated in the previous step; (ii-d) vertical displacement is computed as the integral of the velocity; (ii-e) \( h \) is the amplitude of the vertical displacement during the single stance (from contralateral FC to final IC); and (ii-f) antero-posterior displacement \( d \) is computed using equation

\[
d = 2\sqrt{2L_e h - h^2} + 0.75F
\]

The VTI \( (M_3) \) is also based on circular motion models (Figure 1, right). The COG vertical position describes a circular movement during a step. The minimum vertical acceleration is produced when the COG is in its highest position. This value of acceleration is the sum of the gravity acceleration and the normal component resulting from the rotation movement, which is related to the antero-posterior velocity (assumed constant for each step). Step length is computed as the velocity times the step time (VTI, 2006). The requirements are (1) subject’s effective leg length \( (L_e) \) and (2) IC event detection. The procedure is as follows:

i. Steps are segmented using IC events.

ii. For each step: (ii-a) vertical acceleration is low-pass filtered by means of an FIR filter (10-ms moving average); (ii-b) the minimum value of the vertical acceleration is detected; (ii-c) antero-posterior velocity is computed for each step according to equation

\[
v = 2\sqrt{L_e g - \text{min} a_z}
\]

where \( \text{min} a_z \) is the minimum of the vertical acceleration; and (ii-d) antero-posterior displacement is computed according to \( d = vt \), with \( r \) being the step duration.

Quarter root \( (M_4) \) is an empirical model. The vertical acceleration range in the COG is related to the step length by an empirical model (Weinberg, 2002). The requirements are (1) IC step event detection and (2) correction factor \( (K) \). The procedure is as follows:

i. Steps are segmented using IC time events.

ii. For each step: (ii-a) vertical acceleration is low-pass filtered (3 Hz) by a fourth-order Butterworth filter; (ii-b) maximum and minimum values of the acceleration are detected; and (ii-c) antero-posterior excursion is computed according to expression

\[
d = K\frac{\text{max} a_z - \text{min} a_z}{4}
\]

Signal and data processing was carried out in the same way for each method. For each excursion,

1. Times of first IC event at the beginning and at the end of the central 20-m path were visually identified using the camcorders. Acceleration signals outside those segments were discarded.

![Figure 1 — Biomechanical steps models: Zijlstra/M_1 (left), SiMuR/M_2 (center), and VTI/M_3 (right). L_1, L_2, and L_e stand for different leg length measurements; IC_r/IC_l stands for initial contact (IC, right/left foot); FC_r/FC_l stands for final contact (FC, right/left foot); d and h stand for antero-posterior and vertical COG displacement, respectively; G and a_z stand for gravity and vertical COG acceleration; and V_x stands for the antero-posterior velocity.](image)
2. Raw acceleration was aligned to the anatomical reference frame by means of a rotation and a scale of the acceleration vector (Moe-Nilssen, 1998).

3. Steps were detected and gait events identified (described below).

4. Gait events and vertical acceleration component were used to compute the estimated traveled length using the four analyzed models. Two models \(M_3\) and \(M_4\) depend on a training parameter \(L_e\) and \(K\) respectively. These training parameters were experimentally adjusted using the relation between the actual traveled distance and the raw distance estimated by the method for a test excursion for the same subject. This test excursion was randomly chosen from the 12 available for the subject excluding the excursion under processing.

An algorithmic procedure based on the descriptions of events in acceleration patterns given by Zijlstra and Hof (2003) and Auvinet and colleagues (2002) was applied. The first stage in our algorithm is to compute the main harmonic of the vertical acceleration using a 30th-order, zero-lag, low-pass FIR filter with a cutoff frequency of 2.5 Hz. This filtered signal is used to locate the maximum of the vertical acceleration. For each maximum higher than 10 m/s², a step is identified. Initial contacts are marked at the maximums of the antero-posterior signal, which immediately precede a vertical acceleration maximum. Final contacts are detected as local minimums in a small neighborhood after each vertical acceleration maximum. The FC that follows a given IC corresponds to the contralateral foot. Figure 2 shows an example of the application of the detection method for a given individual.

The distance walked in each excursion was different. Results were evaluated in percentage terms, using the relation between the estimated and the actual walked distances. Accuracy and precision were evaluated for each estimator. For this work, accuracy is defined as the mean of the estimations. Precision is defined as the standard deviation of the estimations. Statistical tests were run to compare the performance of the estimators. Grubb’s test was used to check for outliers. Lilliefors’s test was used to test the normal distribution hypothesis. This knowledge allowed us to select correct hypothesis tests. Accuracy was compared using a Kruskal–Wallis test because data were not normally distributed. A multiple comparison test based on Tukey’s honestly significant difference criterion was run when significant differences were found. Precision was compared through paired \(F\) tests for equal variances where normality of estimations could be assumed. Levene’s robust test was used to compare precision in other cases. Significance levels of 0.01 were used throughout the analyses. The Matlab Statistical Toolbox was used for the analysis.

Results

Each participant completed 12 excursions as designed, and 5580 steps were analyzed. The number of detected steps was correctly computed for all the individuals as validated using the panoramic camcorder. Event detection results for every step were plotted and visually inspected. For two individuals, patterns of antero-posterior and vertical acceleration were very irregular and differed very much from the theoretical acceleration pattern, being difficult to affirm the validity of the algorithm (see Figure 2). Coefficient values of the variability of the step duration for these individuals were 9.36 ± 1.43% and 4.46 ± 1.04% respectively. These two individuals were excluded from the analysis. For the remaining 14 subjects, 7 excursions

![Figure 2](image-url) — Vertical accelerations \((a_z)\) and antero-posterior \((a_x)\) for two subjects. In the first case (left), the accelerations present the patterns described in the literature, which permits the correct detection of the gait events. In the second case (right), said patterns do not appear, leading to great uncertainty in the location of the events.
from 2 subjects were eliminated because the algorithm reported several (3 or more) false detections per trial. Coefficient values for these subjects were 5.40 ± 3.02 and 4.72 ± 3.08% respectively.

The number of false detections in the remaining valid 161 trials was six ICs and eleven FCs out of 4675 steps. Thus, the accuracy of the software reached 99.6%. All FC false detections corresponded to the same subject. With this reduced data set, the number of steps to complete an excursion was of 29.00 ± 2.81. Traveled distance was of 19.92 ± 0.28 m. Step length was thus 0.69 ± 0.07 m. Step duration was of 0.52 ± 0.06 s. Excursion speed was 1.36 ± 0.23 m/s.

The effective leg lengths used for $M_1$ varied approximately between 39 and 50 cm. The correction factor $K$ used in $M_1$ showed a mean value of 0.32. Its standard deviation (interindividual variation) was situated in 0.15. The intraindividual variation, calculated as the mean of the standard deviation of the different values of $K$ used for one individual, took the value of 0.04.

Under these experimental circumstances, an ideal pedometer (without errors in the computation of the steps), adjusted for each subject according to the common procedure based on the mean step length in one of the walks at preferred speed, chosen randomly, would give estimations of 99.25 ± 7.83% of the actual walked distance.

Grubbs’s test reported no outliers for estimations with $M_1$, $M_2$, $M_3$, or $M_4$. Lilliefors’s normality test supported the normal distribution for $M_1$ ($p = .04$), $M_2$ ($p = .22$), and $M_4$ ($p ≥ .5$); $M_3$ estimations were not normally distributed ($p = .01$).

Precision was 6.24% for $M_1$, 5.55% for $M_2$, 8.79% for $M_3$, and 3.07% for $M_4$. Precision for $M_1$ was not significantly different from $M_2$ precision (Bartlett, $p = .14$), whereas it significantly differed from $M_3$ (Levene, $p = 0$) and $M_4$ (Bartlett, $p = 0$). Precision significantly differed also from $M_4$ precision (Levene, $p = 0$). The Levene test also revealed that precision for $M_1$ was not significantly different than precision for an ideal pedometer ($p = .19$). For the remaining methods, precision was better than that of an ideal pedometer (Levene, $p = 0$ for each method).

Accuracy was 103.66% for $M_1$, 100.96% for $M_2$, 100.26% for $M_3$, and 99.99% for $M_4$. Confidence intervals for the mean at 0.01 level showed that only $M_1$ excluded the right value of 100%: $M_1$ (102.37%, 104.96%); $M_2$ (99.81%, 102.11%); $M_3$ (98.44%, 102.09%); and $M_4$ (99.35%, 100.87%). Results for the mean of the same pedometer would also contain the 100% value (97.62%, 100.87%). Accuracy significantly differed between methods (Kruskal–Wallis, $p = 0$). A multiple comparison at 0.01% significance level showed $M_1$ central tendency estimation to be significantly different from others.

**Discussion**

Results of the study are limited by two experimental conditions: the sensor placement and the type of displacement. The sensor was placed in a zone close to the L3 vertebra (through the use of a corset)—superficial approximation to the COG during this type of displacement. Motivations were that descriptions of the models and documented validations (Fang et al., 2005) are mainly based on COG accelerations, with the exception of $M_4$, whose new placement was decided for experimental consistency. The behavior of the models at other points of the waist would require a specific study. However, since the pelvis is a rigid segment, it would be possible to relate the accelerations at different points, making the models applicable in other locations.

It is not clear if the models analyzed are applicable for any type of displacement. Therefore, experiments were restricted to a stable displacement on flat terrain and in a straight line. The only variability permitted (necessary for the study), was that each subject walked with different step (gait) lengths, indirectly achieved by means of the specification of varying the displacement velocity in different walks. Despite these restrictions, straight ahead displacement is one of the most common of human behavior, oscillating according to the activity between 50% and 92% of the time (Glaister, 2006). Given that this displacement can be considered stable after 3 steps (Hase & Stein, 1998), the results of this work are, without doubt, interesting when referring to the ambulatory estimation of the distance walked.

For the evaluation of the models, it is necessary to detect the events within the step. In this work we have decided to tackle the detection by processing the COG accelerations, given that the use of other highly reliable devices (e.g., foot-switches) would be unviable from the point of view of the simplicity of a device. A method has not been found in the literature that permits the detection of the considered IC and FC events. For that reason we have decided to resort to our own implementation based on the previous work (Zijlstra & Hof, 2003; Auvinet et al., 2002).

The acceleration patterns for two individuals differed from the reference pattern shown in the literature. Likewise, deviations were also present in certain excursions for two other individuals. After analyzing the causes, it was discovered that one of the subjects with sporadic irregular walks had run during the initial steps of such walks. For the other subjects, no apparent visual causes for the deviations were appreciated. Coefficient values for these four individuals were situated well above values reported to be normal (Danion et al., 2003; Terrier et al., 2005). All of these anomalous excursions have been eliminated from the analysis. Once discarded, the coefficient values of the variability of the step duration are consistent with what is reported in the literature, which indirectly supports the idea of satisfactory event detection (the duration of the steps, as each excursion is stable, must coincide with these margins). Nevertheless, some walks with sporadic IC erroneous detections have been conserved. The reason for this is that only sporadic and small deviations in the detection of the event are involved, never more than one per walk. With regard to the false detections of the FC, less attention has been paid to them.
as they are only necessary for one model and no more than two misdetections were found per trial.

The final accuracy of the event detection software reached 99.6%, compatible with similar works (Brandes et al., 2006). Nevertheless, we have only reported the feasibility of an event detection approach based on results found in the literature. Previous results in treadmill walking confirm that with some subjects and some conditions the signal shape and regularity can vary significantly (Zijlstra & Hof, 2003), thus making a deeper study necessary to obtain robust event detection algorithms. We defer this for further work.

The implementation of the four methods was consistent with the original authors’ descriptions. For $M_1$ and $M_3$, some particularizations have been carried out derived from the imprecision of their description. However, we believe that they do not differ from the underlying idea of the reported model. In particular, $M_1$ is based on an effective leg length ($L_2$) adapted to each individual and for $M_3$, it is necessary to calculate a $K$ factor relation between the estimated and the actual distance. Given the absence of recommendations to calculate such parameters, we decided to follow an experimental adjustment, comparing the covered distance with that calculated by the model for a test walk chosen randomly. The use of a range of distances, together with the double integration of the whole signal. The results for each step will only be available after this time. It also requires, as well as the detection of each IC event, 4 filter processes (two for the low pass zero-lag and two for the high pass zero-lag) at about 10 s of the signal, together with the double integration of the whole signal.

Methods $M_1$, $M_2$, and $M_3$ have similar memory and computational requirements. Both can be applied step by step, and both need event detection (IC and FC for $M_3$, only IC for $M_3$). The difference between detecting one event or two is not very high, as the complexity of calculation is associated with the initial filtering of the signal necessary to proceed to the detections. The computational cost of the double integral, necessary for the $M_3$ method, is roughly the same as that for the moving average filter necessary for the $M_3$ method.

The method with the least complex implementation is $M_1$. It only requires segmenting the gait, in any event (which would permit the use of zero crossing techniques simpler than those used in this study). The Butterworth filter can be implemented recursively, with a computational cost inferior to the filters employed by the other methods.

Finally, the implementation of the models in real devices could make it necessary, in the event that it was shown that they are not applicable in other conditions, to determine from the data if the displacement is on flat, stable ground and in a straight line. Both the stability of gait and the straightness of the walk could be treated by means of the coefficient of variability of their duration (Danion et al., 2003; Terrier et al., 2005). On the other hand, the determination of the flatness of the terrain should be addressed. In addition, the precise positioning close to the COG seems, a priori, a disadvantage when compared with the traditional pedometers, placed anywhere on the waist. However, the positioning of the pedometers is usually advised in a specific zone of the hip, which would diminish this supposed disadvantage. Finally, dispensing with the corset and attaching the device in a less precise way (e.g., on a conventional belt) could lead to a degradation of results, although this has not been analyzed in depth.
Methods present correct mean estimations. The main deviation is found with $M_1$ that tends to overestimate, where a factor of 1.21 should have been used in place of the proposed 1.25. The deviation could be due to the fact that we are dealing with a different population or perhaps to experimental conditions divergent from those that led to the previous values. For $M_1$ and $M_2$, this result is to be expected, as individual adjustment procedures have been used whose principal effect is to adjust the central tendency. For $M_2$, this is a good result, as it does not depend on individual adjustments external to the method or arbitrary constants. This means an improvement in the step modeling. These results do not mean a significant improvement of accuracy with regard to those expected from an ideal pedometer. This is coherent with the experiments undertaken, as using the adjustment based on the preferred speed (medium length step), the overestimations for low speeds (short steps) would be compensated by underestimates for faster speeds (long steps).

All the methods with the exception of $M_4$ present a precision significantly different from that of an ideal pedometer. This is due to the fact that they incorporate into their formulation mechanisms that try to model step variability. In the case of $M_1$ and $M_2$, these mechanisms are explained by means of biomechanical models, known for a long time, which relate vertical displacement of COG with the antero-posterior. Their principal merit lies in supplying procedures to evaluate such models from the vertical acceleration of the COG measurement through sensors. In the case of $M_4$, it has been impossible to find in the literature a biomechanical justification that supports its behavior. Its possible basis may derive from known facts such as that the extent (range) of the vertical acceleration varies (increases) with the velocity of displacement (Zijlstra & Hof, 1997), in turn directly related to the step length (Margaria, 1976). With regards to $M_4$, precision values lead to doubts about the aptitude of the model and the description of the authors. There are no contrast references that permit the comparison of our results with previous experimentation. Reported results only show the most accurate measuring result (VTI, 2006).

The precision of $M_1$ (6.05%) is similar to the values reported in (Brandes et al., 2006). Although they report a standard deviation (3.3%) half that of our experiments, this is due to the fact that they applied an individual correction factor for each subject. $M_1$ precision does not significantly differ from $M_2$ precision. A possible explanation is that the fundamentals of both methods are very similar, precision being limited by the inexactitude of the pendular analogy of the gait. $M_2$ presents the best precision value, at 3.07%, which situates the estimations in a range of ±9.2%. Previous work (Fang et al., 2005; Weinberg, 2002) reports estimations in a range of 8% for different subjects with different leg lengths, totally consistent with our results.

Applied in the experimental conditions, by means of the use of a step length induced from one of the experiments of preferred velocity chosen at random, a conventional pedometer would present a precision of 10.29%. The results are better than those reported in the literature for commercial pedometers (Crouter et al., 2003), due to the ideal application conditions, where there is no loss of steps and, also, it is applied in strictly controlled, stable step conditions.

In conclusion, we would like to state that in this work four methods for walk distance estimation from COG accelerometry have been implemented and compared. They all are based on step length estimation, and three of them ($M_1$, $M_2$, and $M_4$) are more accurate than what can be expected by a pedometer. Methods $M_1$ and $M_4$ are universal in the sense that they do not require an initial individual experimental calibration. They are both similarly accurate and precise, but $M_1$ is more difficult to use in real time because of its computational requirements and because it is based on a multiplication factor that is not precisely stated. $M_4$ is a heuristic method that requires an individual calibration based on experiments previous to its use, but is the most precise and requires the lowest computational resources. So, the decision about which method is the best for a specific application should solve the dilemma posed by the necessity of calibration procedures versus the precision and computational requirements.

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References


