A Smartphone Approach for the 2 and 6-minute Walk Test

Nicole A. Capela-*IEEE Member*, Edward D. Lemaire, *IEEE Member*, and Natalie C. Baddour, *IEEE Member*

Abstract—**The 2 and 6-minute walk tests (2-6MWT) are used by rehabilitation professionals as a measure of exercise capacity. Our research has produced a new 2-6MWT BlackBerry smartphone application (app) that can be used to run the 2-6MWT and also provide new information about how the person moves during the test.**

The smartphone is worn on a belt at the lower back to record phone sensor data while walking. This data is used to identify foot strikes, calculate the total distance walked and step timing, and analyze pelvis accelerations. Information on symmetry, walking changes over time, and poor walking patterns is not available from a typical 2-6MWT and could help with clinical decision-making.

The 2-6MWT app was evaluated in a pilot test using data from five able-bodied participants. Foot strike time was within 0.07 seconds when compared to gold standard video recordings. The total distance calculated by the app was within 1m of the measured distance.

Keywords—Acceleration, walking, distance estimation, pattern classification, wearable monitoring, rehabilitation.

I. Introduction

In a healthcare environment, exercise capacity measurement is important for understanding a person's current status and evaluating rehabilitation improvement. The 2 or 6 minute walk test (WT) is a common clinical tool for this purpose, where the distance walked in 2 or 6 minutes is measured. A smartphone with integrated sensors provides a platform for wearable biomechanical applications. Wearable analysis during the WT increases the available information derived from the test with minimal additional setup, thus providing clinically useful and immediate information for evaluating physical function and gait at the point of patient contact.

A. *Wearable-Sensor Based Step Detection and Gait Analysis*

Wearable sensors, such as gyroscopes, pressure sensors, and accelerometers, can be attached to a person's body to record motion. In a clinical environment, wearable sensors allow a person to walk freely at a self-selected and natural pace, which is more representative of daily living than some laboratory conditions [4].

Many studies have used accelerometers for gait detection and computing parameters such as cadence, step timing, and symmetry [2], [4], [5]. A wide range of sampling frequencies has been used to record human movement. For counting steps or monitoring energy expenditure, the sampling frequency is not critical and can be lower than 10 Hz [1], [6]–[8]. However, when accelerometers are used for more complex gait pattern analysis, sampling rates range from 50-200 Hz [2], [9].

Actibelt® is a commercial product in the complex analysis category, using a 3D accelerometer sampling at 100Hz. This accelerometer is incorporated into a belt buckle to record accelerations close to the body's centre of mass [10]. Several clinical tests have been programmed for Actibelt®, including the 6MWT. However, this requires the purchase and familiarization with specialized commercial equipment.

Yang et al. achieved accurate foot strike detection using a 25 Hz sampling rate, however detection was not fully automated since missed steps were added manually by the user through visual inspection of the acceleration plot and incorrectly identified steps were removed [2].

Accelerometer data obtained during walking can be segmented into gait cycles [3]. A stride begins when one foot hits the ground and ends when the same foot hits the ground again, while a step begins with a foot strike and ends at the opposite foot strike. Many methods have been used to recognize gait patterns and count steps. The most commonly used signals for step detection are vertical acceleration and anterior-posterior acceleration, since both display prominent peaks at each step [9]. Each signal's cyclical nature allows step identification using the peak amplitude and the time between each peak or zero crossing.

Amplitude can be used to set a minimum threshold that, when surpassed, identifies a step [6], [8], [9], [11], [12]. The time between each step is often used to set a time-frame during which a second step is not expected ("locking period") [7]–[9], [13]. The manner in which peaks are identified and the criteria used to identify steps differs from study to study.

Marschollek et al. [5] compared various step counting algorithms on healthy and mobility-impaired participants. Algorithms that adapted to the periodic acceleration patterns, rather than relying on a-priori knowledge of the gait signals, were more adaptable to mobility-impaired participants. None of the algorithms performed particularly well, with error rates higher than those reported by the original researchers in the literature. More complex pattern

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Nicole Capela is with the Ottawa Hospital Research Institute, Ottawa, Canada and a MASc candidate in Biomedical Engineering, University of Ottawa, Ottawa, Canada (e-mail: ncape055@uottawa.ca).

Edward Lemaire is with the Ottawa Hospital Research Institute, Ottawa, Canada and the Faculty of Medicine at the University of Ottawa, Ottawa, Canada (email: elemaire@toh.on.ca).

Natalie Baddour is with the Department of Mechanical Engineering, University of Ottawa, Ottawa, Canada (email: nbaddour@uottawa.ca).

classification algorithms were recommended to recognize steps in samples with differing motion characteristics.

B. *Calculating Distance Walked*

Distance traveled can be found through double integration of accelerometer measurements. However, this requires careful calibration, extensive computation, and works best when the accelerometer is mounted low on the person's body (i.e., on the foot)[14] .

Distance may also be estimated by stride length, using empirical relations with other measurements such as leg length, change in acceleration, and step frequency. The estimated stride length is multiplied by the number of strides to determine the distance traveled. Empirical relationships from various studies, such as the Weinberg algorithm, rely on calibration to the individual from experimental walking data [14]. This requires leg length or subject height for inverse pendulum models [7], [15] or determination of constants through walking trials [11], [14].

Mean step length can be reliably estimated when the distance walked is known [16]. Since the 6MWT is performed on a track of known length, the mean step length combined with the number of steps detected is a feasible way of estimating the distance walked on the last length.

The WT is a simple test that requires minimal equipment and is implemented regularly to evaluate a person's physical capacity. With the emergence of multiple sensors in smartphones, these wearable computing platforms can be used to easily and quickly provide more information on how the person moves. This information could lead to a better understanding of the person's functional status and thereby improve clinical decision-making.

The purpose of this study was to evaluate the performance of the WT smartphone app for detecting foot strike and calculating distance walked. The study also investigated other relevant biomechanical parameters that can be extracted from smartphone sensors and used in a clinical environment.

II. METHODS

A. *Data Collection*

A pilot study was conducted with five able-bodied participants. Each person performed one 2-Minute Walk Test trial at The Ottawa Hospital Rehabilitation Centre (TOHRC).

Participants walked back and forth along a 25m section of a hallway, covering as much distance as possible in 2 minutes. Each 25m length covered is referred to in this paper as a "walkway". Some people were asked to stop during a walkway to evaluate the app's ability to detect this event. At the end of the test, the distance walked on the last walkway was measured using measuring tape and recorded on a data sheet.

Before testing, a belt with a rear pocket was secured around the person's waist so that the pocket was at the middle of the pelvis. A Blackberry Z10 smartphone was placed upright in this rear pocket, facing outward. Accelerometer, gyroscope and magnetometer data were sampled on the Z10 at approximately 50Hz, using the TOHRC Data Logger [17].

Every trial was video recorded using a separate BlackBerry 9900 smartphone. Foot strikes, number of steps counted, turns, and contextual information were extracted from the digital video as a gold-standard comparator.

Sensor data were imported into a custom Matlab program to calculate outcome measures. These measures were compared with the gold standard outcomes.

B. *Primary Outcome Measures*

The following parameters were calculated from sensor data: total distance walked, total number of steps, number of steps per length, average (AVG), standard deviation (SD) of cadence, AVG, SD of step time (left and right steps), AVG, SD of stride time, and step time symmetry (left and right steps).

Cadence was calculated from the number of steps per walkway time, disregarding steps during turns. Symmetry was the difference between consecutive left and right step times, divided by the bilateral average [4].

C. *Data Processing and Algorithm*

1) *Turns*

For the 2 minute walk test, the person walks back and forth. Therefore, turns must be identified to accurately divide the data into walkways. These walkways were analyzed separately and steps during turns, which did not contribute to the distance walked, were not counted.

Turns were identified using the BlackBerry azimuth signal. This signal automatically corrects itself to stay between 0 and 360º, which causes rapid changes in magnitude (Figure 1). This was corrected in software before detecting turns.

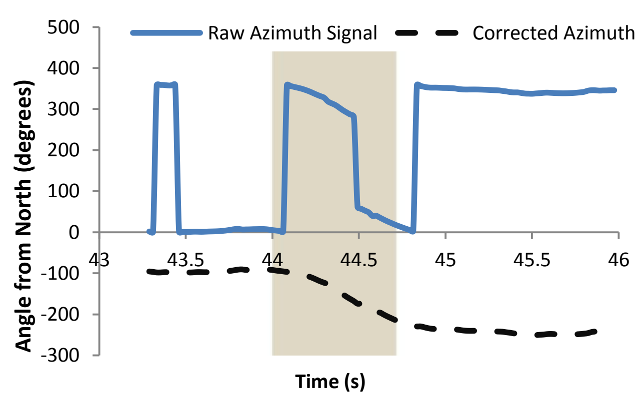

Figure 1: Raw and corrected Azimuth signals (turn highlighted)

A turn was detected if a change of more than 100º in azimuth occurred in a 3 second window. The turn duration was defined as the azimuth signal with a SD greater than 10º per 1 second data section. These were reliable ranges for turn detection at different walking speeds.

2) Step Detection

Steps were detected using Anterior-Posterior (AP) linear acceleration, since peaks in the forward signal were found to coincide with foot strike event [18]. The signal was filtered using a fourth-order zero-lag Butterworth low pass filter with cutoff frequency of 6 Hz, since 99.7% of walking signal power is contained below 6 Hz [19].

The most reliable methods for accurate foot strike detection involved detecting acceleration signal peaks, typically with accelerometer sampling rates in the range of 100Hz [9], [20]. In this study, a combination of a locking period and peak detection were used, with a 50Hz sampling rate. First, the step duration was calibrated using a 5 second walking sample from the beginning of the trial. The length between consecutive positive zero crossings in the filtered AP acceleration signal were measured.

Since the AP signal sometimes fluctuated from a zero baseline, experimentally determined thresholds were used to select the max or mean step duration, and what fraction of this duration to use as the locking period. Initial thresholds were also set to detect the first and last steps in a length, since these tended to have lower peak values than other steps because the person is starting up from a stop or slowing down for a turn. These thresholds were calculated by subtracting mean from maximum in the 5 second sample.

The filtered AP acceleration was searched using a moving window with size based on the step duration. Only one step could be detected in each window, and was identified as the maximum peak in AP linear acceleration. Different people produced AP signal peaks of different amplitude. In addition, these peaks could be sharp and short, rounded and longer, or asymmetrical, depending on the person's gait pattern. Thus, step identification was based on signal shape similarity to other identified steps in the same walk, rather than pre-assigning thresholds. The minimum value within the window, before and after each peak, was found. A peak was only identified as a step if the difference between the peak and the minimum on either side were both within 35% of the same calculated values from the previous step.

If the duration between 2 consecutive steps was greater than 1.75 times the previous step duration, the filtered AP acceleration signal between the 2 steps was searched again for missed steps using different criteria. If an AP signal peak within this range matched the timing pattern of previous steps or if a vertical acceleration peak passed a threshold, a step was identified. If no missed steps were identified, the period was considered a stop and the data were excluded.

Foot strike time was identified as the maximum peak in the raw AP linear acceleration within the neighborhood of each detected step. The raw signal had occasional gaps in time and also flat-lined for small sections. These sections were detected and ignored. If one of these sections occurred where a step was expected, step occurrence was estimated using the walkway's average step time.

3) Left and Right Steps

Left and right steps were identified using the LR linear acceleration. This signal was filtered using a fourth-order zero-lag Butterworth low pass filter with cutoff frequency of 1 Hz, as shown in Figure 2. Lower cutoff frequencies greatly reduce signal noise, but can distort the signal [19]. Since the filtered LR signal was used to identify the person's direction of motion during a step, this distortion was acceptable.

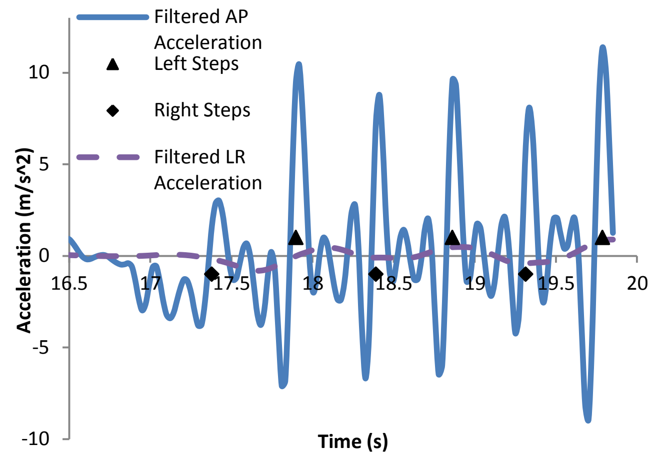

Figure 2: Filtered acceleration signal with left and right step identification

The LR signal fluctuated from a zero baseline, with left steps identified as concave (person accelerated to the right during swing phase after a left step) and right as convex. At each detected step, the tangent to the filtered LR linear acceleration signal was calculated at 25% of the step after foot strike (i.e., peak LR acceleration). If the tangent was above or below the curve, the signal was considered concave or convex, respectively. A pattern was identified and used to fill in the steps that were not identified as left or right, as well as to correct double counts. This information was used to calculate the primary outcome measures.

4) Distance walked

The distance walked on the last length was calculated by multiplying the number of steps by the average step length of the previous walkway. If a stop was detected in the previous walkway, the average step length of the third last walkway was used. To ensure that the average step length used to calculate distance was similar to the step length in the last walkway, the ratio of mean step timing on the last walkway to the mean step timing of the second last walkway was calculated. If the ratio was less than 0.9 (i.e., more than 10% increase in mean step time), the average step length was multiplied by this ratio, then by the number of steps to determine the distance walked.

D. Data Analysis

Foot strike times were compared to the gold standard video. Smartphone video was synchronized with the sensor data by the first accurately detected foot strike event. The total distance calculated was compared to the total distance measured.

III. RESULTS

Foot strike time was within 0.07 seconds (i.e., within ± one video frame) when compared to the gold standard. The total distance calculated by the app was within 1m of the measured distance, as shown in Table 1.

Table 1: Comparison of Measured and Calculated Distance

Participant	Total Distance (m)		Difference (m)
	Measured	Calculated	
1	200.69	200.71	0.02
2	150.98	151.35	0.37
3	164.57	164.84	0.27
4	159.29	158.80	0.49
5	192.66	193.33	0.67

IV. DISCUSSION

The 2 and 6 minute walk tests are used to evaluate physical capacity. These tests are administered periodically during a rehabilitation program to assess improvement. According to discussions with rehabilitation physiotherapists, a calculated distance within 1m of the actual distance is sufficiently accurate, since an improvement of less than 1m after rehabilitation is not considered clinically significant.

The video was recorded at a frame rate of 30 frames per second. Since the real foot strike could have occurred one frame before or after the closest frame captured by the camera, a tolerance of 2 frames, or 0.07 seconds was allowed for step detection. Ten steps out of a total of 1116 steps for all 5 subjects were not identified within this tolerance, and these were a result of irregular signals or blurry video recordings. Stops and left and right steps were correctly identified when compared to video recordings.

V. CONCLUSION

Currently, the only measure obtained from the WT is the total distance walked during the time interval. With a minimal increase in setup time, the 2 or 6-minute Walk Test app provides quantitative biomechanical information that describes how a person moves and may provide a better understanding of the person's functional exercise capacity and walking quality.

The Blackberry Z10 smartphone, with a 50Hz sampling rate and sensors, was appropriate for the data acquisition task. This outcome should be repeatable for other smartphone platforms.

The app's additional information may be useful for physiotherapists and physiatrists when evaluating the results of therapy and guiding clinical decision-making. Research is currently under way to validate the app with a larger sample of able-bodied participants and with people receiving rehabilitation therapy.

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