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Validity of proximity sensor-based wear-time detection using the ActiGraph GT9X

Diego Arguello[1], **Kristie Andersen**[1], **Alvin Morton**[1], **Patty S. Freedson**[3], **Stephen S. Intille**[1,2], and **Dinesh John**[1]

[1]Bouve College of Health Science, Northeastern University Boston, MA.

[2]College of Computer and Information Science, Northeastern University Boston, MA.

[3]Department of Kinesiology, University of Massachusetts, Amherst, MA.

Abstract

Purpose: To investigate the performance of proximity sensor-based wear-time detection using the GT9X under laboratory and free-living settings.

Methods: Fifty-two volunteers (23.2±3.8 y; 23.2±3.7 kg/m^2) participated in either a laboratory or a free-living protocol. Participants in the lab wore and removed a wrist-worn GT9X on 3–5 occasions during a 3-hour directly-observed activity protocol. The 2-day free-living protocol used an independent temperature sensor and self-report as the reference to determine if a wrist and hip-worn GT9X accurately determines wear (i.e., sensitivity) and non-wear (i.e., specificity). Free-living estimates of wear/non-wear were also compared to the Troiano 2007 and Choi 2012 wear/non-wear algorithms.

Results: In lab, sensitivity and specificity of the wrist-worn GT9X in detecting total minutes of wear-on and off was 93% and 49%, respectively. The GT9X detected wear-off more often than wear-on, but with a greater margin of error (4.8±11.6 *vs.* 1.4±1.4 min). In the free-living protocol, wrist and hip-worn GT9X's yielded sensitivity and specificity of 72 and 90% and 84 and 92%, respectively. GT9X estimations had inferior sensitivity but superior specificity to Troiano 2007 and Choi 2012 algorithms.

Conclusions: Due to inaccuracies, it may not be advisable to singularly use the current proximity-sensor-based wear-time detection method to detect wear-time.

Corresponding Author: Dinesh John, Ph.D.; 316 Robinson Hall, Northeastern University 360 Huntington Ave. Boston, MA 02115 USA; Telephone: 1-617-373-5695; d.john@neu.edu.
Diego Arguello, M.S.; 520 Behrakis Health Sciences Northeastern University 360 Huntington Ave. Boston, MA 02115 USA; Telephone: 1-970-581-0095; Arguello.d@husky.neu.edu
Kristie Andersen, B.S.; 520 Behrakis Health Sciences Northeastern University 360 Huntington Ave. Boston, MA 02115 USA; Telephone: 1-860-861-5046; andersen.k@husky.neu.edu
Alvin Morton, M.S., 520 Behrakis Health Sciences Northeastern University 360 Huntington Ave. Boston, MA 02115 USA; Telephone: 1-631-742-3638; amorto16@vols.utk.edu
Patty S. Freedson, Ph.D., 109 Totman Bldg, Amherst, MA-01003 ; Telephone:413-545-2620; psf@kin.umass.edu
Stephen S. Intille, Ph.D., Northeastern University 910-177 (9th Fl (Office 924) 360 Huntington Avenue Boston, MA 02115 USA; Telephone: 617-373-3711; S.Intille@northeastern.edu

Disclosure of interest

The authors report no conflicts of interest.

Keywords

Wear-time; Physical Activity Assessment; Accelerometry; Multi-sensor

Introduction

Assessing human behaviors [e.g., physical activity (PA)] using accelerometers is increasingly common in research (Freedson, Bowles, Troiano, & Haskell, 2012; Montoye, Moore, Bowles, Korycinski, & Pfeiffer, 2016). However, accelerometers continuously detect and record data even when it is not worn. Studies including population level investigations [e.g., NHANES (*National Health and Nutrition Examination Survey Data*, 2016) and the Women's Health Study (Lee & Shiroma, 2014)] using ActiGraph monitors (ActiGraph Corp, LLC, Pensacola, FL.), have relied on activity-count-based algorithms [e.g., Troiano 2007 (Troiano et al., 2008) and Choi 2012 (Choi, Liu, Matthews, & Buchowski, 2011)] or self-report logs to determine monitor wear-time. ActiGraph activity-count-based wear-time detection techniques are prone to errors because they rely solely on summarized motion signals to distinguish between wear-time inactivity and true non-wear. Continuous zero activity counts during monitor non-wear may not be discernible from similar values during wear-time inactivity (i.e., sitting still or sleeping) (Mâsse et al., 2005). Similarly, relying solely on activity counts to discern wear-time will yield errors during non-wear when a sensor records motion artifacts (e.g., vibrations). Current motion-based algorithms may also be sensitive to: (i) monitor location, and (ii) algorithm-specific thresholds of zero activity counts to define a period of non-wear (Choi et al., 2011; Choi, Ward, Schnelle, & Buchowski, 2012; Hutto et al., 2013; Mâsse et al., 2005; Troiano et al., 2008).

To improve wear-time sensing, ActiGraph's GT9X uses a capacitive proximity sensor that detects skin contact. This sensor combined with a motion data threshold is used to distinguish between wear and non-wear. To our knowledge, proximity sensor-based wear-time sensing using the GT9X has not been validated. This study determined the accuracy of wear-time sensing using the GT9X under controlled laboratory, and uncontrolled free-living conditions. The study also validated the activity count-based Troiano 2007 and Choi 2012 wear-time detection algorithms and compared these estimates to wear-time detected by the GT9X sensors.

Methods

Fifty-two volunteers (33 males and 19 females) participated in this study (mean ± SD: age= 23.2 ± 3.8 years, BMI= 23.2 ± 3.7 kg/m^2). Twenty-six participants each participated in the lab-based and free-living protocols. All volunteers provided written informed consent approved by the Northeastern University Institutional Review Board.

Experimental Protocol

ActiGraph GT9X wear-time sensing—The GT9X monitor (3.5 × 3.5 × 1 cm; 14 g) has a polycarbonate enclosure (thickness= 1.2 mm; dielectric constant= 2.9) and the capacitive proximity sensor (32 × 11.5 mm) is located inside and next to the backside of the device (opposite display screen). The proximity sensor is manufactured 'in-house' and is a single electrode connected in a circuit with two port pins, which alternate between driving a 192 kHz signal and sensing a change in that signal. This alternating signal duty cycle charges the electrode and forms a 0.022μF capacitor with a sensitivity of 4.2 nF (personal communication with Doug Cross, Director of Engineering, ActiGraph). The charge in the capacitor varies with the type of material (e.g., air, human body) in close proximity or in contact with the sensor. Each time the GT9X is initialized, the GT9X is calibrated to establish a reference signal of this capacitor in free air. Through in-house experimentation, ActiGraph determined that a charge differential of 43 nF from the free air reference is indicative of skin-contact. I.e., a charging time differential of 52 microseconds. However, wear-time sensing using the GT9X is deliberately biased towards positive wear detection when motion is detected by the 8 g GT9X accelerometer. When this sensor detects an acceleration of at least 0.04 g lasting at least 0.125 s, the differential threshold of the proximity sensor that returns positive skin contact is halved. Reliance on motion was introduced in the firmware update 1.4.0. for the GT9X. The 6 monitors used in this study had firmware 1.5.0. or higher. The microcontroller in the GT9X measures differences in charging time at the end of a whole round minute, once every 60 seconds. Thus, the resolution of distinguishing between wear and non-wear using the proximity sensor-based method is 1-min. For optimal wear-time detection, ActiGraph recommends that the casing holding the GT9X be worn in contact with the skin.

Lab Protocol—This protocol aimed to examine if the GT9X detects instances (i.e., exact minute) when the device was removed and worn again. I.e., to validate the operational principle of the proximity-sensing technology used to detect skin-contact, which is primarily used to distinguish wear from non-wear. The device was inserted into the plastic compartment of the 'Link Watch Band' (*Link Watch Band*) and worn snugly on the participant's non-dominant wrist. The lab-protocol to test wear-time sensing using the GT9X was part of an ongoing study to calibrate body-worn sensors. The protocol consisted of a 3-hour simulated routine consisting of ambulatory and free-living PA and sedentary behaviors. During the lab-protocol, a researcher removed the GT9X on 3 to 5 random occasions. The researcher carried the sensor in his/her pocket during periods of non-wear. A second researcher recorded the exact minute the sensor was removed and worn again using a custom time-stamp annotation software on a handheld tablet that was synced to the GT9X. These direct observations were used as the criterion to evaluate the GT9X in detecting actual wear-time.

Free-Living Protocol—The free-living protocol compared wear-time detected by the GT9X and two popular count-based algorithms (i.e., Troiano 2007 and Choi 2012) to a reference measure derived using a combination of an independent temperature sensor (Dwyer Series BDL Button Data Logger, Dwyer Instruments Inc.) and self-reported monitor wear-on/off time. Participants wore one GT9X on the dorsal aspect of the non-dominant wrist and another on the anterior axillary line above the iliac crest for approximately 2 days. We examined performance on the hip as it is the preferred wear-location in most studies. The hip-elastic belt was inserted through the GT9X 'Link Holster' (*Link Wrist Holster*) such that the belt lay over the face of the device and the Link Holster was in direct contact with the skin. Location of wear (left *vs*. right) was counterbalanced among participants. Participants were: (i) instructed to use the display on the GT9X to self-report monitor wear-on/off times, and (ii) made aware of the need to immediately and accurately record on/off time, and its impact on study findings.

The BDL is a small (17.1 mm diameter, 6.4 mm height) lightweight (4 g) sensor that records kinetic temperature between −30 to 70 ^{0}C with an accuracy of ± 1 ^{0}C, each minute. The BDL was secured to the wrist and hip straps such that it was in direct contact with the skin on the ventral and medial sides of the wrist and hip GT9X monitors, respectively. To detect points in time (i.e., minute) when the GT9X was removed (‘wear-off’) from the wrist/hip and worn again (‘wear-on’), temperature readings were plotted versus time and overlaid with self-reported wear periods graphed as fixed square-waves. The objective temperature sensor was considered as the primary indicator for when the GT9X was worn and removed, while the over-lapping self-report was used to verify the occurrence of a non-wear bout. Wear-on was the minute when skin surface-temperature began to rise rapidly (i.e., increasing slope) towards normal values (i.e., 32–37 ^{0}C) (Benedict, Miles, & Johnson, 1919; Bierman, 1936) verified by self-report. Similarly, wear-off was the time-point when temperature readings began to drop rapidly (i.e., decreasing slope) from normal skin surface-temperature verified by participant self-report. This visualization method showed a clear temperature differential of approximately 10 ^{0}C between wear-on (32–37 ^{0}C) and off (20–25 ^{0}C).

During the lab and free-living protocols, the wrist and hip devices were worn snugly to maximally maintain contact with the skin. To increase periods of non-wear in the free-living protocol, participants were instructed to remove the wrist and hip monitors during lunchtime each day, during water-based activites, and during sleep each night. This yielded at least two occasions/day of monitor removal followed by once again wearing the GT9X.

Free-living snug vs. loose wear sub-study

Given that the GT9X relies greatly on its proximity sensor to determine wear-time, a potential source of error over extended periods is a participant’s personal preference in wearing the sensor strap. If an individual is uncomfortable with a snug strap, he/she may loosen it, which may result in periods of poor-to-no contact between the device and the skin. To determine if strap tightness affects the accuracy of proximity sensor-based wear-time sensing, 8 participants from the free-living sample completed an additional 24-hr free-living protocol. Participants continuously wore a GT9X on each wrist except when showering. One strap was worn such that the device was snug and could not move on the wrist (tight condition). The second was worn such that it was loose enough to move only on the dorsal aspect of the wrist (loose condition). If a device was removed and worn again during the protocol, the participant wore the strap using the same buckle-tongue adjustment used prior to device removal. The reference for this sub-study was derived using the temperature sensor and self-report method described earlier.

Data Analyses

Monitor outputs were processed using ActiLife software (v6.13.4; ActiGraph Corp., LLC) to create 60 s epoch files. ActiLife provides a visual display of minute-by-minute activity counts summarized into periods of wear and non-wear and a time-stamped spreadsheet of the same. Free-living data from each sensor was also processed to provide outputs of wear/non-wear detection using the Troiano 2007 and Choi 2012 algorithms. ActiLife enables automated analyses using the default parameters of these two algorithms with the option of using either vertical axis or triaxial vector magnitude activity counts. We used vector magnitude activity counts because it yields improved wear/non-wear detection (Choi et al., 2012). Statistical analyses were conducted using SAS 9.4 (SAS Institute Inc. NC, USA). Level of significance (where applicable) was set at $p < 0.05$.

Controlled Lab Protocol—To determine if GT9X proximity sensor-based wear-time estimation correctly identifies instances of wear-on and off, we quantified the total number and proportion of directly-observed true instances (exact minute) identified by the sensor. Early detections by the GT9X were those wear-on/off instances detected before the directly-observed instance. Delayed detections were those detected after a directly-observed instance. Durations of early and delayed detections were quantified as the absolute error in minutes between the instance detected by the GT9X and the corresponding true instance. Analyses on estimating durations (in min) of wear and non-wear included sensitivity (proportion of wear-time minutes correctly identified as such), specificity (proportion of non-wear-time minutes correctly identified as such), positive predictive value (PPV, wear detection precision), negative predictive value (NPV, non-wear detection precision) and overall accuracy [(true wear + true non-wear)/total minutes]. We did not compare the performance of the GT9X against the Troiano 2007 and Choi 2012 algorithms because most wear and non-wear periods in the lab-protocol were too short to exceed the activity count algorithmic threshold that classifies a bout of time as non-wear (Choi et al., 2012; Troiano et al., 2008).

Free-Living Protocol—Similar to the lab-protocol, we computed the sensitivity, specificity, PPV, NPV and overall accuracy in detecting durations of wear and non-wear by the GT9X at the wrist and hip. Similar metrics were also computed for wear and non-wear detection by Troiano 2007 and Choi 2012 algorithms. Additionally, we computed the bias (total duration of wear and non-wear misclassification error) and precision (95% CI of the error) for these methods.

To compare the performance of snug and loose wrist-worn devices in detecting wear-time, we computed total wear-time and bouts detected during each condition and compared these to actual wear-time and bouts using the non-parametric Kruskal-Wallis H Test with Dunn's multiple comparisons tests.

Results

Lab-Based Protocol

There were a total of 162 directly observed instances for wear-on and off (5.2 ± 1.8 per subject). In all, the wrist-worn GT9X wear-time sensor recorded a total of 136 (84.0%) instances when the device was put on or removed. However, among these, wear-on was accurate for only 11 (16.2%) instances and wear-off for one instance. Among the 55 inaccurate detections of wear-on, 13 instances (19.1% of total wear-on detections) were early detections, while the remaining 42 instances (64.7% of total wear-on detections) were recorded after a delay. The mean duration of early and delayed detection for wear-on was 10.4 ± 6.5 min (95% CI: 13.9 to 6.9 min) and 1.4 ± 1.4 min (95% CI: 1.0 to 1.8 min), respectively. Among the 67 inaccurate detections of wear-off, 4 instances (5.9% of total wear-off detections) were early detections, while the remaining 63 instances (92.6% of total wear-off detections) were recorded after a delay. The mean duration of early and delayed detection for wear-off was 6.3 ± 5.7 min (95% CI: 11.9 to 0.6 min) and 4.8 ± 11.6 min (95% CI: 1.9 to 7.6 min), respectively.

The wrist-worn ActiGraph GT9X had a sensitivity of 93.3% ± 9.2% (95% CI: 89.7%, 96.8%), specificity of 48.6% ± 34.3% (95% CI: 35.4%, 61.8%), PPV of 74.6% ± 17.3% (95% CI: 67.9%, 81.2%), NPV of 68.4% ± 36.4% (95% CI: 54.4%, 82.4%), and overall accuracy of 75.7% ± 15.7% (95% CI: 69.6%, 81.7%). The mean duration for true wear and non-wear bouts were 16.2 ± 8.3 min and 15.0 ± 11.9 min, respectively. In comparison, the wrist-worn GT9X estimated wear and non-wear bouts with a mean duration of 27.1 ± 23.9 and 12.9 ± 9.4 min, respectively.

Free Living Protocol

Table 1 contains sensitivity, specificity, PPV, NPV, and overall accuracy of wear/non-wear classification performance of the wrist and hip-worn GT9X proximity sensor-based estimation and the Troiano 2007 and Choi 2012 algorithms. The mean durations for total true wear and non-wear in the free-living protocol for both wrist and hip-worn devices were 22.5 ± 4.8 and 13.8 ± 3.2 hours, respectively. The wrist-worn GT9X proximity sensor-based method detected 17.6 ± 8.9 and 18.7 ± 7.3 hours of wear and non-wear, respectively. Conversely, the Troiano 2007 and Choi 2012 wear-time algorithms detected 23.1 ± 6.3 and 13.2 ± 4.0 hours and 23.3 ± 6.1 hours and 13.0 ± 4.1 hours of wear and non-wear for the wrist worn GT9X, respectively. Similarly, the hip-worn GT9X proximity sensor-based estimation method detected 20.0 ± 6.4 and 16.2 ± 6.1 hours of wear and non-wear, while the Troiano 2007 and Choi 2012 algorithms detected 22.5 ± 6.7 and 13.8 ± 4.6 hours, and 23.1 ± 6.7 and 13.2 ± 4.7 hours of wear and non-wear, respectively.

Snug *vs.* loose sub-study

There were no statistically significant differences among actual wear-time (23.9 ± 2.6 hours) and the snug (23.3 ± 2.3 hours) and loose (23.0 ± 1.8 hours) conditions [χ^2 (2) = 2.545, p = 0.280]. The loosely worn GT9X underestimated actual wear-time by 51.3 ± 37.0 min (95% CI 78.7, 23.8 min), and the snugly worn GT9X underestimated actual wear-time by 37.6 ± 61.6 min (95% CI 83.2, 8.0 min) per 24-hour measurement period. However, there were statistically significant differences [χ^2 (2) = 10.085, p = 0.0065] among the total actual wear bouts and bouts detected by the snug and loose conditions. Dunn's multiple comparisons tests showed that compared to the reference, the loose condition yielded a significantly higher number of wear bouts [7.0 ± 5.4 bouts (95% CI: 3.3, 10.7 bouts), p= 0.006]. Conversely, the reference measure was not significantly different from bouts detected during the snug condition [0.5 ± 0.8 bouts (95% CI: 0,1 bouts), p= 0.625].

Discussion

Accuracy of GT9X Wear-time sensing

Proximity sensor-based wear-time estimation using the GT9X primarily relies on determining physical contact/proximity between the device and human skin. Wear detection thresholds for the proximity sensor is secondarily modified based on movement detected by the GT9X accelerometer (i.e., a raw acceleration threshold). The lab-protocol empirically examined the operational principle of the primary technology (proximity sensor) used to detect skin contact. The 2-day and the 24-hour snug *vs.* loose experimental protocols examined how operational accuracy translates to practical free-living applications.

The GT9X performed unsatisfactorily in detecting exact instances of wear-on and off conditions in the lab-protocol. This may be attributable to inadequacies of ActiGraph's parameters for the proximity sensor-based method to detect '*true*' skin contact. Factors such as temperature and humidity may alter the characteristics of the copper-based electrode in the proximity sensor and cause a drift in the sensor's baseline reference values, and thereby the signal-to-contact thresholds to detect skin proximity. To counter such drift, the GT9X firmware is coded to enable the device microcontroller to adjust the stored reference value by a small amount every time a measurement returns a non-wear-detection (personal communication with Doug Cross, Director of Engineering, ActiGraph). This adjustment lies within a hard coded capacitance range between 1000 nF to 3370 nF (determined by ActiGraph as the capacitance range of the human body). Adjustments will occur until a positive wear-detection is found or the abovementioned capacitance limits are reached. Early and late detections may occur if the device is worn and removed frequently (e.g., lab-protocol) because the drift-logic in the GT9X firmware may adjust the reference value in the wrong direction. Since proximity sensor measurements are made only once a minute, the adjustment period may last several minutes before the firmware identifies the correct direction in which the adjustment must be made. A factor that may have further confused the drift-logic in the firmware may be the placement of the GT9X in the pocket of the research assistant where human skin is separated from the sensor by a layer of clothing. Subsequent researcher movement when conducting the protocol may have influenced the proximity of the device to the layer of clothing that is flush with the skin. However, the likelihood of this is low because (i) the sensitivity of the proximity sensor is insufficient to detect the proximity of the skin through clothing and (ii) we independently tested and confirmed the inability of the proximity sensor to determine skin-contact over clothing.

The above-mentioned technical shortcomings did not impact the sensitivity of the GT9X proximity sensor-based method in the lab-protocol. This may be due to a much higher proportion of delayed instance detection with a smaller margin of error (1.4 ± 1.4 min) than early detections (78% *vs.* 22%), which allowed most true wear-time minutes to be captured as such by the GT9X. Conversely, poor specificity (49%) in the lab-protocol may be attributable to a high proportion of instances (93%) being detected late, with a large margin of error (4.8 ± 11.6 min). Although a delay may have been present in the free-living protocol, it is likely that it did not impact free-living specificity to the same extent because the delay is proportionally smaller to the total wear-off duration (average bout= 4.9 ± 4.5

hours) itself. Proximity-based wear-time estimation also seemed to yield slightly improved performance on the hip as compared to the wrist. This may be due to a potentially higher frequency of sensor displacement at the wrist (even when snug) during daily activities.

Poor wear-time detection may arise from various physiological and environmental factors that alter the capacitance of the proximity sensor electrode in the GT9X. The most common source of error is a lack of sustained physical contact between the skin and the device. While we found that the GT9X underestimates actual wear-time in both snug and loose conditions, the loose condition produced larger total wear-time duration detection error and a higher number of bouts for wear-time. Thus, the resulting partial or complete absence of skin contact in the loose condition was sufficient to impair the detection of true monitor wear.

Study findings indicate a need for additional human testing to refine the existing parameters for the GT9X proximity sensor-based method to distinguish between wear and non-wear in free-living studies. Additionally, inaccuracies may be attenuated through periodic on-chip calibration of the proximity sensor during periods of non-wear to reset drifting baseline values. Figure 1 depicts the individual 'best' and 'worst' performances when the GT9X is worn loosely as compared to the corresponding snug and reference measures.

Free-living GT9X proximity sensor-based wear-time vs. activity count algorithms

In the 2-day protocol, performance of GT9X wear-time sensing was inferior to the Troiano 2007 and Choi 2012 algorithms. Sensitivity of GT9X wear-time sensing was lower than the Troiano 2007 and Choi 2012 algorithms by approximately 8 to 22% at both the hip and wrist sites. Proximity sensor-based wear-time estimation by the GT9X overestimated the total number of bouts of true wear-time by 7.2 ± 10.0 bouts (~2 times the reference) on the hip and 14.5 ± 18.7 bouts (~4 times the reference) on the wrist, and overestimated non-wear by 7.9 ± 10.2 bouts (~2 times the reference) on the hip and15.3 ± 18.8 bouts (~3 times the reference) on the wrist. In comparison, the Troiano 2007 algorithms detected 90.0% ± 30% of wear bouts on the hip and 84.4% ± 24.8% on the wrist, and 49.4% ± 24.2% of non-wear bouts on the hip and 49.2% ± 21.3% on the wrist. Similarly, the Choi 2012 algorithm detected 71.5% ± 27.5% of wear bouts on the hip and 70.1% ± 23.9% on the wrist, and 43.4% ± 21.5% of non-wear bouts on the hip and 44.1% ± 19.4% on the wrist. The overestimation of the GT9X compared to the underestimation of Troiano 2007 and Choi 2012 algorithms may be due to small periods of false positive non-wear being detected by the proximity sensor-based method in the absence of necessary skin contact. This factor will not affect count-based wear-time detection methodologies.

Interestingly, the GT9X proximity sensor-based estimation misclassified a substantial portion of wear-time as non-wear, which ranged from 9.7% to 17.8%, but misclassified non-wear as wear-time by only 3.2% to 3.7%. Contrarily, Troiano 2007 and Choi 2012 algorithms misclassified a greater amount of non-wear as wear-time ranging from 5.1% to 5.8% and 5.8% to 6.6%, respectively, but still had lower misclassification of wear-time as non-wear [Troiano 2007: 1.3% to 5.5%; Choi 2012: 1.1% to 4.8%].

Conclusions

While promising, capacitive proximity sensing in the GT9X needs to be significantly improved to detect true non-wear and wear-time. Given our findings, it may not be advisable to singularly use the GT9X proximity sensor-based method to distinguish between monitor wear and non-wear. Underestimating true wear-time may not only result in incorrect estimates of PA and sedentary behavior, but may also lead to the exclusion of subjects from data analyses when applying monitor wear-time inclusion criteria (e.g. valid day > 10 hrs/day) for capturing habitual PA behavior (Mathews, 2005; Matthews et al., 2001; Troiano et al., 2008).

Limitations of the GT9X capacitive proximity sensing technology may warrant supplemental measures to identify true wear-time. For example, since this method relies greatly on the proximity of the sensor electrode to the skin, vibrations/movements (e.g., snug *vs.* loose wear), or when using ActiGraph's hip-clip that requires an additional layer (clothing/belt) between the GT9X case and the skin may impair accuracy. Complex sensor data-fusion methods that integrate raw acceleration with capacitive proximity sensing may yield improved estimates of wear-time. This may require increasing the frequency of measurement of the proximity sensor from once a minute to every 15 or 30 seconds and access to proximity sensor raw data. The latter will allow researchers to rigorously test and refine the sensor's threshold that discriminates non-wear from wear. Future iterations of the GT9X could leverage the display screen to include active wear-time sensing by soliciting feedback from study participants in real-time, thereby eliminating some ambiguity in detecting wear-time. Alternatively, incorporating additional sensors such as temperature or non-touch proximity sensors (e.g., optical sensors) may yield improved estimates of wear-time

Strengths and limitations

To our knowledge, this study is the first to (i) validate the proximity sensor-based wear-time estimation using the GT9X and (ii) comprehensively validate the Troiano 2007 and Choi 2012 wear-time algorithms in free-living against a refined reference measure that uses an objective physiological sensor supplemented with self-report. Previous free-living validation of Troiano 2007 and Choi 2012 wear/non-wear motion algorithms relied on a diary-record as a reference (Choi et al., 2012). Another strength is that the study examined wear-time in different scenarios including wear sites and conditions. Weaknesses include a short free-living sample of 2 days and the absence of a hip-worn-device in the lab-protocol.

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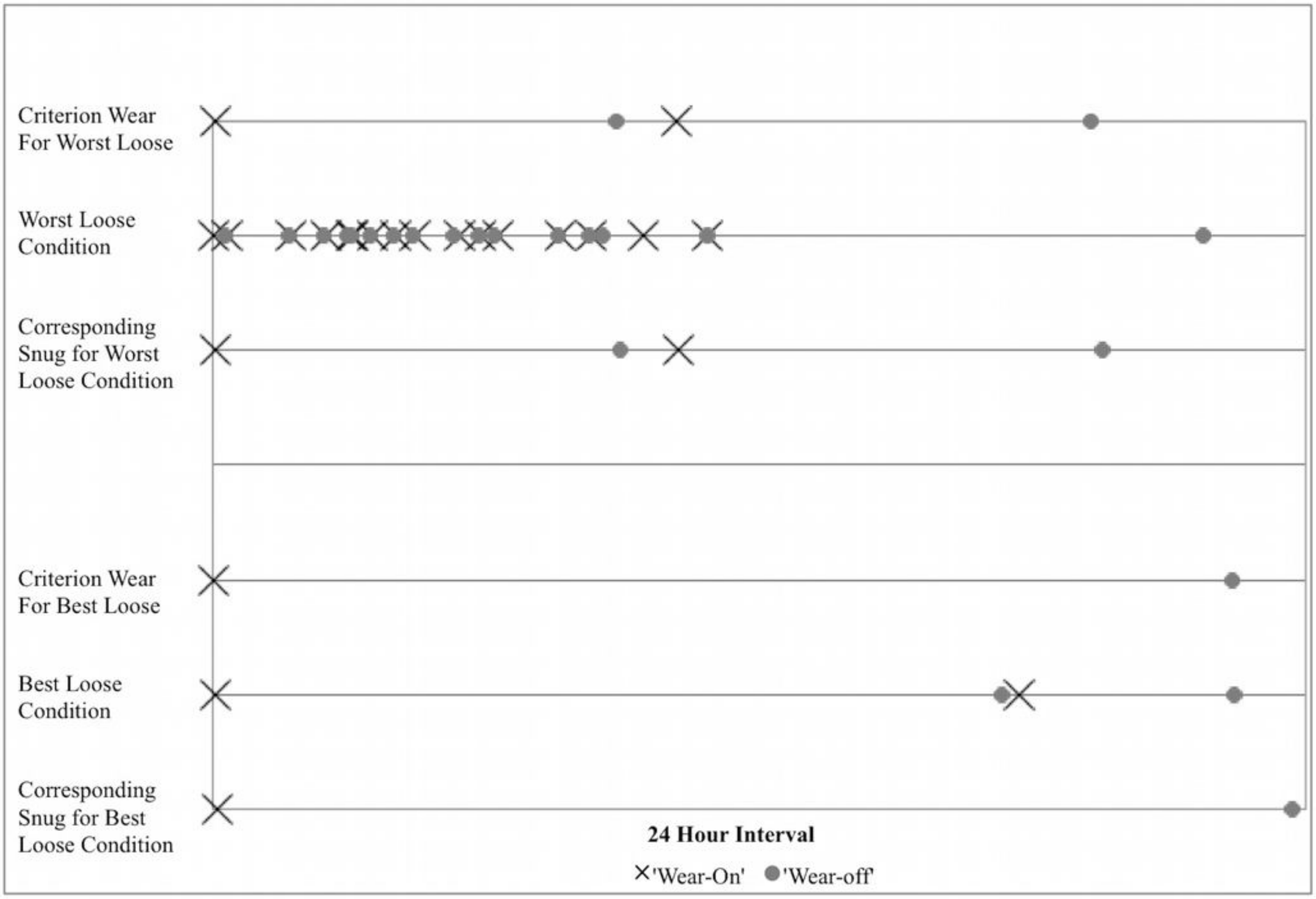

Figure 1.

Individual worst and best performance of the wrist-worn GT9X proximity sensor-based method in detecting wear *vs*. non-wear during the loose condition. Loose wear may result in a high number of false-positive, wear-off detections that result in an increase in wear-on and wear-off bouts and misclassifications of wear-time minutes.

Table 1.

Mean, standard deviations, 95% confidence intervals of the performance of the GT9X proximity sensor-based estimation and the Troiano 2007 and Choi 2012 algorithms in detecting wear-time at the wrist and hip.

1A	Sensitivity	Specificity	PPV	NPV	Accuracy
GT9X	71.6 ± 28.4% [60.3, 83.0%]	90.2 ± 19.6% [82.3, 98.0%]	93.1 ± 8.1% [89.8, 96.3%]	70.8 ± 23.6% [61.4, 80.3%]	78.5 ± 17.5% [71.5, 85.5%]
Troiano 2007	92.9 ± 13.7% [87.5, 98.4%]	86.0 ± 8.2% [82.7, 89.3%]	91.4 ± 5.2% [89.3, 93.5%]	91.7 ± 12.2% [86.8, 96.6%]	90.5 ± 7.9% [87.3, 93.6%]
Choi 2012	93.3 ± 13.5% [87.9, 98.7%]	84.0 ± 8.3% [80.7, 87.3%]	90.1 ± 5.7% [87.8, 92.4%]	92.2 ± 12.6% [87.2, 97.2%]	89.9 ± 8.0% [86.7, 93.1%]

1B	Sensitivity	Specificity	PPV	NPV	Accuracy
GT9X	84.43 ± 22.5% [75.4, 93.4%]	92.1 ±14.7% [86.2, 97.9%]	94.0 ± 9.8% [90.1, 97.9%]	82.8 ± 21.5% [74.1, 91.4%]	87.1 ± 16.4% [80.6, 93.7%]
Troiano 2007	90.9 ± 18.2% [83.6, 98.2%]	86.2 ± 7.4% [83.2, 89.2%]	90.8 ± 6.0% [88.4, 93.2%]	90.1 ±14.5% [84.2, 95.9%]	89.3 ± 10.6% [85.0, 93.5%]
Choi 2012	92.2 ± 17.9% [85.1, 99.4%]	83.5 ± 7.9% [80.4, 86.8%]	89.6 ± 5.9% [87.2, 91.9%]	91.9 ± 14.2% [86.2, 97.6%]	89.2 ± 10.4% [85.0, 93.4%]

Table 1A and B. Mean, standard deviations, 95% confidence intervals of the performance of the GT9X proximity-sensor-based sensing and the Troiano 2007 and Choi 2012 algorithms in detecting wear-time at the wrist and hip, respectively. PPV= positive predictive value; NPV= negative predictive value.