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Validation of the Polar H10 Accelerometer in a Sports-Based Environment †

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Abstract: The Polar H10 is a low-cost wearable with a heart rate monitor and tri-axial accelerometer with potential for many applications. While the device's heart rate monitor has been widely studied, there is no research validating the accelerometer specifically. The purpose of this study was to conduct a validation of the Polar H10 accelerometer to establish static and dynamic validity during a sports-based task. Static validity was determined by computing the relative error when using a level guide to hold each axis of the Polar H10 against gravity. Fifteen healthy adults (8F/7F) participated in sports-based tasks while wearing the Polar H10 (Polar Electro, Poland) and a comparison device, the MetaMotionR inertial measurement unit (MbientLab Inc., USA). Dynamic validity was characterized using Pearson's correlation coefficient and root mean square error (RMSE). Additionally, common features in human activity recognition (mean magnitude, root mean square, power, and signal magnitude area) were computed in 2s windows and compared via RMSE and Wilcoxon rank sum tests. When held against gravity, the Polar H10 had relative errors ranging from 2.620% to 4.288%, suggesting high static validity. During sports-based tasks, the accelerometers had correlations between 0.888 and 0.954, indicating sufficient concurrent validity for all axes, as well as acceleration magnitude. The differences in acceleration features were minimal (RMSE for mean, root mean square, power, and signal magnitude were 0.003 G, 0.004 G, 0.112, and 0.017 G, respectively), but all reached significance ($p < 0.001$). These results provide evidence for the use of the Polar H10 accelerometer to measure movement during sport-like activities.

Keywords: accelerometer; validation; heart rate monitor; activity recognition; physical activity

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1. Introduction

Usability [1–3] and cost [4] are barriers to the widespread uptake of wearable sensing systems. The growth of the commercial wearable market presents an opportunity to overcome both of these challenges. Consumer-grade devices can be more user-friendly than those employed in research, which often require longer set up times [5] and are more expensive. However, it is important to establish the accuracy and reliability of all wearable devices, as these factors directly impact data interpretation and the utility of technologies developed using these sensors (i.e., algorithms and machine learning classifiers) [1].

The Polar chest band is a consumer-grade low-cost wearable that has previously been validated for heart rate monitoring in adults [6–8] and children [9]. A recent version of the device, the Polar H10, also features a tri-axial accelerometer. While the use of the sensor (in conjunction with Polar Team Pro software) to measure speed and distance has been investigated [10], the use of the accelerometer has yet to be validated. The purpose of this work was to conduct a validation of the Polar H10 tri-axial accelerometer under static and dynamic conditions that may support its use in research and technology development.

2. Methods

Fifteen healthy adults were recruited from Holland Bloorview Kids Rehabilitation Hospital via email lists and word of mouth. Individuals over 18 years of age with normal or corrected-to-normal vision and hearing were eligible for the study. Although no screened participants were excluded, individuals with pre-existing cardiovascular conditions, a recent musculoskeletal injury (up to 10 days before the study session), and/or a condition or injury that could be aggravated by exercise were not eligible for the study. This research was approved by the Bloorview Research Institute Ethics Board (eREB #2020-0305) and the University of Toronto. Written informed consent was obtained from each participant.

To collect raw accelerometer data, the Polar H10 (Polar Electro, Finland) was connected to the Polar Sensor Logger app (Jukka Happonen, available on the Google Play Store) via Bluetooth to log data at 200 Hz with a range of 16 G.

Static validity of the Polar H10 accelerometer was assessed by holding the device against a level surface guide with each axis aligned to gravity for 30 s. Accelerometer data were averaged, then relative error between the accelerometer values and expected value (1 G) were computed. Since Kolmogorov-Smirnov normality tests reached significance, Wilcoxon rank sum tests were used to evaluate whether the static validity of the accelerometer changed after the study session, during which the accelerometer experienced a period of high-intensity movement.

For testing under dynamic conditions, Polar H10 measurements were compared to the MetaMotionR (Mbientlab Inc., USA), an inertial measurement unit that has previously been validated against motion capture systems [11]. Data was logged directly on the MetaMotionR at 200 Hz with a range of 16 G. The MetaBase App (Mbientlab Inc., USA) was used to configure the MetaMotionR and transfer data. The Polar H10 and MetaMotionR were synchronized by tapping them on a table three times. Participants wore the Polar H10 around the chest as described in the device user manual [12]. The MetaMotionR was placed just below the Polar H10 on the participants' torso using a skin-safe adhesive (Cover-Roll Stretch, BSN Medical, USA) directly on the skin, followed by the MetaMotionR with a stronger tape overtop (Leukotape P, BSN Medical, USA) to minimize loosening of the adhesives and sensors as the participants started to sweat.

After placing sensors and going through a brief warm-up, participants performed semi-structured tasks simulating anticipated movements in a sports-based assessment under development [13]. During the study, participants performed 34 shuttle-runs in an 8 m^2 to 9 m^2 space. The shuttle-run activity was layered with a cognitive task (e.g., touching buttons in a specific sequence) such that the following dynamic movements were elicited: walking, running, lunging, shuffling, stopping/pausing, changing direction, and accelerating/decelerating [14]. Each study session lasted approximately two hours.

Dynamic validity was assessed by calculating the Pearson's correlation coefficient between the Polar H10 and MetaMotionR for each acceleration vector and the overall magnitude under raw and filtered conditions [15–17]. Low-pass zero-lag 4th order Butterworth filters with differing cut-off frequencies (10 Hz, 20 Hz, 30 Hz, and 40 Hz) were examined. To explore the application of the sensor for activity recognition, commonly used features [1] were compared using Wilcoxon rank sum tests. Mean magnitude, root mean square (RMS) of magnitude, power of magnitude, and signal magnitude area (SMA) were calculated over 2 s intervals then compared using the root mean squared error (RMSE) between the features from each accelerometer and Wilcoxon rank sum tests.

3. Results & Discussion

3.1. Participants

Fifteen individuals (8F/7M) participated in the study. Table 1 summarizes the age ranges of the participants. Using the Godin-Shephard Leisure-Time Physical Activity Questionnaire, two participants were identified as inactive (score of less than 14), four were moderately active (score between 15 and 23), and nine were active (a score over 24) [18].

Table 1. Participant age and biological sex.

Age (years)	Sex	
	Female	**Male**
18–24	5	3
25–34	3	3
34–55	0	1

3.2. Static Validity

The relative error between the Polar H10 reading and expected value (1 G) for each axis is outlined in Table 2. A Wilcoxon rank sum test comparing relative error before and after the high intensity activity found a significant difference for the Z axis ($p = 0.006$), but not the X ($p = 0.36$) or Y ($p = 0.29$) axes.

Table 2. Static relative error (%) for each accelerometer axis before and after high intensity activity.

Axis	Before High Intensity Activity	After High Intensity Activity
X	3.053 (0.466)	2.929 (0.466)
Y	4.288 (0.513)	4.255 (0.505)
Z	2.862 (0.207)	2.620 (0.195)

Under static conditions, the Polar H10 accelerometer had mean relative errors of 2.620 % to 4.288 %. This indicates high static validity, as relative error was less than 5% for all axes [15,16]. While the difference between relative error before and after the sport-like activity was statistically significant for the Z-axis ($p = 0.006$), the magnitude of the difference was minute (a change in RE of 0.252%) and is likely acceptable for most applications.

3.3. Concurrent Validity during Motion

Table 3 highlights the concurrent validity and RMSE for raw accelerometer data during the sports-based task. The highest mean correlation was observed in the overall magnitude ($r = 0.954$) while the lowest was in the y-axis ($r = 0.888$). The lowest RMSE was observed in magnitude (0.141 G), while the highest was in the z-axis (0.273 G).

Table 3. Mean and standard deviations of correlation coefficient (r) and root mean squared error (RMSE) during motion.

Axis	r	RMSE (G)
X	0.891 (0.113)	0.231 (0.119)
Y	0.888 (0.160)	0.182 (0.125)
Z	0.909 (0.085)	0.273 (0.139)
Magnitude	0.954 (0.046)	0.141 (0.069)

Low-pass filtering at different cut-off frequencies led to minor decreases in correlations (Table 4) and increases in RMSE (Table 5). While small, all these differences were significant (Wilcoxon signed-rank test, $p < 0.001$). The largest change was seen at a cut-off frequency of 10 Hz, where the correlation for acceleration magnitude decreased from 0.954 to 0.949 and RMSE increased from 0.141 G to 0.151 G.

Table 4. Mean and standard deviations of correlation coefficient (r) for accelerometer data low-pass filtered at different cut-off frequencies.

Axis	Cut-Off Frequency			
	40 Hz	**30 Hz**	**20 Hz**	**10 Hz**
X	0.891 (0.232)	0.890 (0.144)	0.889 (0.145)	0.887 (0.146)
Y	0.888 (0.160)	0.887 (0.160)	0.886 (0.160)	0.884 (0.162)
Z	0.908 (0.085)	0.908 (0.086)	0.906 (0.086)	0.904 (0.088)
Magnitude	0.954 (0.047)	0.953 (0.047)	0.952 (0.049)	0.959 (0.051)

Table 5 shows a comparison of commonly used activity recognition features calculated from each accelerometer. Distributions for all features were non-normal (Kolmogorov-Smirnov, $p < 0.001$) and Wilcoxon rank sum tests reached significance ($p < 0.001$ for all features). However, the RMSEs between the Polar and MetaMotionR features were less than 0.005 G for RMS and mean and 0.017 G for SMA. Power had the highest RMSE at 0.112 G.

Table 5. Comparison between Polar and MetaMotionR values for features commonly used in activity recognition.

Feature	Polar	MetaMotionR	RMSE
Mean Magnitude (G)	1.098 (0.104)	1.134 (0.113)	0.003
Root Mean Square of Magnitude (G)	1.163 (0.162)	1.215 (0.113)	0.004
Power of Magnitude (n.u.)	1.778 (0.698)	1.945 (0.805)	0.112
SMA (G)	1.524 (0.229)	1.618 (0.233)	0.017

During dynamic sport-like tasks, the Polar H10 and MetaMotionR had mean correlations between 0.888 and 0.954, reflecting a high to very high correlation between the accelerometer signals [19]. With correlations of over 0.7, concurrent validity was found to be sufficient for all axes and for the overall magnitude [15,16]. Filtering led to significant, but small decreases in concurrent validity. Commonly used activity recognition features (mean magnitude, RMS of magnitude, power of magnitude, and SMA) calculated with a window size of 2 s were found to be significantly different between the two devices. However, the magnitudes of the differences were small, especially when considering that the sensors were placed in slightly different locations.

3.4. Limitations

In addition to the slight offset between sensors, correlations between the accelerometers may have been lowered if sensors (especially the tape-secured MetaMotionR) became loose during exercise. While participants were instructed to inform research staff when this happened, correlations decreased in trials leading up to sensor adjustments. In this study, a preliminary validation focused on the correlation between the Polar H10 and MetaMotionR accelerometers as the desired application of the device was to measure acceleration patterns during high intensity activity. Further investigation is needed to validate the Polar H10 accelerometer for other purposes, such as measuring peak impacts during contact sports.

3.5. Comparisons with Previous Work

With mean correlations of over 0.887 relative to the MetaMotionR, the Polar H10 accelerometer performs similarly to other wearable-integrated accelerometers. When comparing the Gear S smartwatch (Samsung Electronics, Korea) accelerometer to the Actigraph GR3X+, Davoudi et al. [20] found that the devices had correlations over 0.89 during shaker table and treadmill tests and over 0.7 for other daily activities. Additionally, when comparing the MinimaxX S4 (Catapult Innovations, Australia) accelerometer to a motion analysis system, Wundersitz et al. [16] found that RMSE between the measures were 0.11 G and 0.23 G during jogging and running tasks. Similarly, the RMSEs reported in the current study ranged from 0.141 G to 0.273 G.

4. Conclusions

The findings of this research suggest that the accelerometer contained within the Polar H10 can measure accelerations with adults during non-contact sports activities. While filtering the data may be beneficial in some applications, it had a minor impact on the concurrent validity and error. These findings open opportunities for future development and use of the Polar H10 as a reliable low-cost, consumer-grade heart rate monitor and accelerometer.

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Conflicts of Interest:

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