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DIABETIC Medicine

LETTER

Detection of real-life activities by a tri-axial accelerometer worn at different body locations: Analysis and interpretation

Modern technologies offer updates and information using Ambient Intelligence (AmI) and personalised user experience. Wearable sensors can collect and process data about lifestyle and health status, integrate them with clinical variables and provide people with simple feedback messages on the adequacy of their behaviors, delivered by wearable devices or home appliances.[1] AmILCare (Ambient Intelligence for Long-term Diabetes Care) is a project aimed at supporting people with noninsulin-treated type 2 diabetes in the day-to-day management of their disease. Daily step counts, physical activity and energy expenditure will be monitored by an FDA-approved medical grade tri-axial accelerometer[2] (GT9X; ActiGraph Corp.), fulfilling EASD/ADA criteria for Digital Technology in diabetes care.[3] The device was tested in healthy volunteers to verify if the above variables are recorded more reliably wearing the device at the wrist or the waist.

Changes in acceleration were recorded at 30-Hz frequency as counts per minute (CPM) for each axis and used to calculate the tri-axial vector magnitude (VM): $\sqrt{axis1^2 + axis2^2 + axis3^2}$.

Energy expenditure was calculated by the Freedson VM3 Combination algorithm[4]: kcals/min $=0.001064 \times$ VM $+0.08751$ (BM) -5.500229, where VM = vector magnitude, CPM = counts per minute and BM = body mass in kg.

Physical activity was classified according to CPM: Sedentary: 0–99; Light: 100–759; Lifestyle: 760–1951; moderate: 1952–5724; vigorous: 5725–9498; moderate-to-vigorous (MVPA): 1952–9498; very vigorous: ≥9499.[5] Steps were counted from the y-axis only.[6] Wear compliance was measured by the Choi algorithm.[7]

Five healthy volunteers, three women and two men, aged 43.0 ± 13.2, BMI 21.58 ± 2.52 wore two GT9X continuously for 7 days, one at the nondominant wrist and the other at the waist, removing them for the shortest possible times. They kept detailed records of their 24-h activities. One-hour lengths of seven different activities of increasing intensity were further analysed. “Watching television”, “reading” and “having lunch/dinner” were taken as sedentary; “car driving/public transport” and “housekeeping” as light; and “bicycling, dancing, gardening and playing soccer” and “walking” as moderate. Data taken at the wrist and waist were extracted from the CentrePoint software and expressed as mean ± SD. Observation was from 0.00 h of the day following instalment of the devices to 24.00 h of the day preceding retrieval. Differences between wrist and waist were checked by t-test for paired data, setting the level of significance at $p < 0.05$.

Wearing compliance was higher at the wrist than at the waist (1419.20 ± 21.92 vs. 1276.25 ± 111.12 min/day, $p = 0.0399$). There was a large discrepancy in calorie expenditure, values at the wrist being fourfold higher (1581.97 ± 428.65 vs. 404.85 ± 195.55; $p = 0.0006$), despite higher step counts at the waist (8263.87 ± 3413.42 vs. 9787.62 ± 3812.67; $p = 0.0395$). The device at the waist recorded more percent total time in Sedentary mode (75.11 ± 6.28 vs. 44.93 ± 3.04; $p = 0.0003$) and less in lifestyle (5.38 ± 2.54 vs. 22.82 ± 3.37; $p = 0.0010$) and MVPA (3.71 ± 1.60 vs. 12.65 ± 3.66; $p = 0.0009$). The activities selected for further analysis were ordered by increasing number of steps, the only variable that did not differ between wrist and waist (Table 1). The device at the wrist recorded higher-energy expenditure and less time in Sedentary mode for all sedentary and light activities, and did not differ from the waist for moderate and more intense ones.

Our results suggests that, in real-life conditions similar to those of noninsulin-treated type 2 diabetes patients that will be involved in the AmILCare project, the GT9X provides more reliable lifestyle data if worn at the waist than the non-dominant wrist. Wrist records grossly overestimated total energy expenditure, whilst measuring similar step counts and more sedentary behaviour, both throughout the day and in selected activities (Table 1), consistent with previous reports.[8] Whilst the waist is mostly steady whilst reading, watching television or having a meal, the wrists may browse through book pages or handle objects and cutlery. When walking, conversely, waist and wrists are somewhat coordinated, resulting in similar CPM. Importantly, the ActiLife step-counting algorithm was originally developed for hip-worn devices.[6]

TABLE 1 Recordings of seven different real-life activities by GT9X monitors worn at the nondominant wrist and at the waist

	Sedentary: watching TV	Sedentary: reading	Sedentary: lunch/ dinner	Light: housekeeping	Light: driving/public transport	Moderate: dancing, cycling, soccer, gardening	Moderate: walking
Step counts							
Wrist	38.20 ± 31.07	37.00 ± 33.65	129.40 ± 198.93	321.00 ± 367.30	489.00 ± 271.00	2257.00 ± 1633.29	2822.60 ± 925.88
Waist	36.60 ± 30.56	80.40 ± 77.44	158.40 ± 135.28	440.20 ± 359.94	516.80 ± 341.94	2448.40 ± 2135.77	4044.20 ± 2206.28
Ratio	1.04	0.46	0.82	0.73	0.95	0.92	0.70
p value	0.9267	0.1157	0.6465	0.1771	0.4926	0.6821	0.1075
Energy expenditure (calories)							
Wrist	37.06 ± 26.61	40.87 ± 15.02	107.39 ± 59.80	126.41 ± 46.93	86.73 ± 40.36	169.55 ± 85.98	173.23 ± 52.91
Waist	1.99 ± 0.92	4.50 ± 2.50	6.48 ± 5.37	19.87 ± 19.41	22.95 ± 12.44	98.13 ± 99.48	155.14 ± 107.69
Ratio	18.58	9.08	16.58	6.36	3.78	1.73	1.12
p value	0.0402	0.0066	0.0162	0.0077	0.0173	0.0775	0.6133
Sedentary activity: (percent of total activity)							
Wrist	40.33 ± 24.87	32.33 ± 14.75	7.00 ± 4.47	12.33 ± 9.10	19.00 ± 6.30	2.67 ± 1.90	3.33 ± 4.08
Waist	89.67 ± 6.81	84.33 ± 10.97	80.67 ± 17.18	52.67 ± 19.42	61.33 ± 12.10	13.67 ± 14.31	14.33 ± 14.56
Ratio	0.45	0.38	0.09	0.23	0.31	0.20	0.23
p value	0.0107	0.0041	0.0003	0.0161	0.0008	0.1290	0.1109
Light activity: (percent of total activity)							
Wrist	35.33 ± 19.98	38.33 ± 12.19	25.33 ± 14.74	16.67 ± 12.69	31.33 ± 17.89	18.67 ± 24.56	9.00 ± 7.23
Waist	9.67 ± 7.01	14.33 ± 10.90	17.00 ± 16.60	33.00 ± 12.99	29.33 ± 14.12	43.00 ± 29.19	20.00 ± 19.08
Ratio	3.66	2.67	1.49	0.51	1.07	0.43	0.45
p value	0.0635	0.0202	0.5584	0.1959	0.8572	0.0364	0.2070
Lifestyle activity: (percent of total activity)							
Wrist	15.67 ± 15.93	20.00 ± 11.37	42.33 ± 9.47	27.33 ± 13.57	23.00 ± 8.28	20.67 ± 7.87	19.00 ± 7.23
Waist	0.67 ± 0.91	1.00 ± 0.91	1.67 ± 1.18	13.67 ± 18.00	4.67 ± 4.31	22.67 ± 12.17	13.33 ± 7.73
Ratio	23.50	20.00	25.40	2.00	4.93	0.91	1.43
p value	0.1065	0.0186	0.0008	0.2785	0.0234	0.7374	0.2457
Moderate activity: (percent of total activity)							
Wrist	8.67 ± 10.76	9.33 ± 8.87	25.00 ± 24.01	41.33 ± 27.52	25.33 ± 15.20	50.67 ± 20.19	66.67 ± 14.67
Waist	0.0 ± 0.0	0.33 ± 0.75	0.67 ± 1.49	0.67 ± 0.91	4.33 ± 3.84	20.67 ± 29.73	52.33 ± 34.57
Ratio	–	28.00	37.50	62.00	5.85	2.45	1.27
p value	0.1461	0.0743	0.0906	0.0299	0.0305	0.0972	0.2124

(Continues)

DIABETIC Medicine

TABLE 1 (Continued)

	Sedentary: watching TV	Sedentary: reading	Sedentary: lunch/dinner	Light: housekeeping	Light: driving/public transport	Moderate: dancing, cycling, soccer, gardening	Moderate: walking
MVPA (moderate-to-vigorous physical activity. Percent of total activity)							
Wrist	8.67 ± 10.76	9.33 ± 8.87	25.33 ± 23.79	43.67 ± 29.02	26.67 ± 16.20	58.00 ± 27.06	68.67 ± 13.30
Waist	0.0 ± 0.0	0.33 ± 0.75	0.67 ± 1.49	0.67 ± 0.91	4.67 ± 4.31	20.67 ± 29.73	52.33 ± 34.57
Ratio	–	28.00	38.00	65.50	5.71	2.81	1.31
p value	0.1461	0.0743	0.0853	0.0295	0.0315	0.0189	0.1986

Note: One-hour recordings sampled for different activities extracted from 24-h records, ordered by increasing number of steps recorded at the waist. Data are expressed as mean ± SD. Differences between means checked by paired *t*-test.

One problem with surveys of physical activity in real life is that most data derive from studies in controlled laboratory conditions of vigorous/very vigorous sports-related activities, whereas data on sedentary and moderate activities in free-living adults are limited. Freedson [4] showed the correlation between the activity counts of a waist-worn ActiGraph and energy expenditure, but since the wrist is considered convenient for comfort and compliance, the National Health and Nutrition Examination Survey and UK Biobank have opted for wrist-worn accelerometers to survey behaviours at population level.[9]

Recently, we reported that people with noninsulin-treated type 2 diabetes will accept technological support if noninvasive and maintaining confidentiality.[10] Whilst the wrist may seem more natural and comfortable (the GT9X doubles into a digital timepiece), our results, despite the small sample, strongly suggest that accelerometers are best worn at the waist to collect plausible data and provide reliable feedback and guidance, if patients are to benefit from appropriate lifestyle adjustment.

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CONFLICT OF INTEREST

None declared.

ETHICS APPROVAL

The study was carried out in accordance with the 2013 Helsinki Declaration and approved by the Institutional Ethics Committees of Città della Salute e della Scienza di Torino and Ordine Mauriziano di Torino (CS2/1316).

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