Physical Activity Classification Using the GENEA Wrist-Worn Accelerometer

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ABSTRACT

ZHANG, S., A. V. ROWLANDS, P. MURRAY, and T. L. HURST. Physical Activity Classification Using the GENEA Wrist-Worn Accelerometer. *Med. Sci. Sports Exerc.*, Vol. 44, No. 4, pp. 742–748, 2012. **Introduction**: Most accelerometer-based activity monitors are worn on the waist or lower back for assessment of habitual physical activity. Output is in arbitrary counts that can be classified by activity intensity according to published thresholds. The purpose of this study was to develop methods to classify physical activities into walking, running, household, or sedentary activities based on raw acceleration data from the GENEA (Gravity Estimator of Normal Everyday Activity) and compare classification accuracy from a wrist-worn GENEA with a waist-worn GENEA. **Methods**: Sixty participants (age = 49.4 ± 6.5 yr, body mass index = 24.6 ± 3.4 $kg{\cdot}m^{-2}$) completed an ordered series of 10–12 semistructured activities in the laboratory and outdoor environment. Throughout, three GENEA accelerometers were worn: one at the waist, one on the left wrist, and one on the right wrist. Acceleration data were collected at 80 Hz. Features obtained from both fast Fourier transform and wavelet decomposition were extracted, and machine learning algorithms were used to classify four types of daily activities including sedentary, household, walking, and running activities. **Results**: The computational results demonstrated that the algorithm we developed can accurately classify certain types of daily activities, with high overall classification accuracy for both waist-worn GENEA (0.99) and wrist-worn GENEA (right wrist = 0.97, left wrist = 0.96). **Conclusions**: We have successfully developed algorithms suitable for use with wrist-worn accelerometers for detecting certain types of physical activities; the performance is comparable to waist-worn accelerometers for assessment of physical activity. **Key Words:** ACTIVITY MONITORS, FAST FOURIER TRANSFORM, WAVELET, CLASSIFICATION, WALKING, MACHINE LEARNING

Physical activity (PA) is important in improving health and reducing risk of disease (18,22,23). Accurate measurement of PA is essential in evaluating the efficacy of interventions and understanding of the relationship between PA and health (5,6,13,29,30). Accelerometers are popularly used in PA monitoring because of their small size, low cost, convenience, the ability to record data for several days (9,19), and assessment of multiple dimensions of PA, e.g., total activity, time spent in different levels of intensity (14,20) and predicted energy expenditure (8,11). Most accelerometry devices used for the assessment of habitual PA are worn on the waist or lower back (16,20). A wrist-worn device is potentially more convenient to wear and hence may lead to greater compliance during prolonged wear; for example, assessment of habitual activity.

The cut point approach is the conventional method of algorithmic design based on accelerometer data (14,36). It is an easy and efficient way to classify different intensities of PA; however, the approach is limited by the use of only the mean count for each user-defined time interval or epoch. The relationship between accelerometer counts and energy expenditure (EE) differs by activity mode; hence, this approach leads to misclassification of activities with similar EE but different counts or similar counts but different EE (27). Alternatively, signal processing methods such as fast Fourier transform (FFT) and discrete wavelet transform (DWT) have been extensively used on streaming data to generate more features to distinguish different types/intensities of PA with a better recognition rate. FFT uses the frequency spectrum analysis to distinguish different types of PA (3,21,25). The shortcoming of FFT is that it does not provide the time at which these frequency components happened. One possible modification is the short-time Fourier transform (STFT), which applies the Fourier transform repeatedly to different time-localized windows. The STFT still requires extra parameter choices, such as window size, to be made (28). Compared with FFT, DWT (or one of its variants) has the advantage that localization can be achieved in both time and scale simultaneously, and it has been used in PA studies to detect walking activities based on data collected from hip/lower back accelerometer (4,32).

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In this study, we developed algorithms for PA classification based on data collected from a wrist-worn accelerometer and compared their performance to the algorithms based on a waist-worn accelerometer. The algorithms are designed to distinguish sedentary, household, walking and running activities. Features were mainly generated from FFT; in addition, two time domain features extracted from DWT were generated to enhance the classification rate. Various machine learning algorithms were tested to select the most accurate and efficient algorithm for PA classification.

METHODS

Subjects. Sixty [23 males (age = 48.9 ± 6.8 yr, body mass index (BMI) = 25.9 ± 2.7 kg·m^{-2}) and 37 females (age = 49.6 ± 6.4 yr, BMI = 23.8 ± 3.5 kg·m^{-2})] volunteers age 40–65 yr were recruited for the study. Fifty-five of the volunteers were right handed and the remaining five were left handed. All participants were free from diagnosed disease and musculoskeletal injury and had no affirmative answers to the PA Readiness Questionnaire (PAR-Q). Ethics approval was obtained from the institutional review board. Written informed consent was obtained from each participant.

Measuring equipment. The GENEA (the commercially available monitor is waterproof and called the GeneActiv and has a ±8-g sensor) is used in this study as a measuring device. The GENEA is an acceleration sensor developed by Unilever Discover (Colworth, United Kingdom), manufactured, and distributed by ActivInsights Ltd. (Kimbolton, Cambridgeshire, United Kingdom). It is a triaxial, ±6*g* seismic acceleration sensor housed in a small (36 × 30 × 12 mm), lightweight (16 g) casing, with a splash-proof design making the GENEA appropriate for wear at multiple body locations. The sampling frequency of the GENEA ranges from 10 to 160 Hz. The battery can last up to 10 d when recording data at 80 Hz. The reliability and validity of the GENEA, when data are integrated into epochs, are comparable with those of the ActiGraph and the RT3 (14).

Data collection procedures. Participants arrived at the laboratory having refrained from consuming nicotine, caffeine, or a large meal for at least 2 h before the study session. They were asked not to exercise for at least 6 h before the appointment. Each participant was asked to complete an ordered series of 10–12 semistructured activities in the laboratory and outdoor environment. The energy expenditure (METs, mean ± SD) associated with each of the activities is shown in brackets after each activity (see Esliger et al. (14) for measurement details). The activities included lying (0.94 ± 0.23 METs), standing (1.13 ± 0.25 METs), seated computer work (1.22 ± 0.29 METs), 4-km·h^{-1} walk (3.88 ± 0.69 METs), 5-km·h^{-1} walk (4.59 ± 0.79 METs), 6-km·h^{-1} walk (5.88 ± 0.98 METs), walking up and down stairs (6.19 ± 1.10 METs), free-living 6-km·h^{-1} walk (5.76 ± 0.94 METs), two household activities [from window washing (3.37 ± 1.06 METs), washing up (2.35 ± 0.45 METs), shelf stacking (4.19 ± 0.98 METs), and sweeping (3.39 ± 0.67 METs)], one run [8 km·h^{-1} (11.13 ± 1.38 METs), 10 km·h^{-1} (12.0 ± 1.24 METs), or 12 km·h^{-1} (13.61 ± 0.6 METs)], and an optional free-living 10-km·h^{-1} run (12.62 ± 1.17 METs). The lying activity was performed for 10 min, whereas all other activities were performed for around 4.5 min.

Throughout testing, three GENEA monitors were worn, one on each of the left and right wrists (using simple watch straps, monitors positioned over the dorsal aspect of the wrists midway between the radial and ulnar styloid processes) and one on the waist (using an elasticized belt, monitor positioned over the right side of the hip, midclavicular line land-marked by the supraspinale). The same three GENEA monitors were used by all 60 participants and were always positioned at the same sites for each participant. Data were collected at 80 Hz and downloaded after each testing session. Around 7% of the data were unavailable for analysis because of a device or initialization fault. Figure 1 is a typical plot of GENEA data for the series of activities carried out by a participant in the laboratory (top panel: waist-worn GENEA; bottom panel: wrist-worn GENEA).

Signal processing and feature extraction. For each type of activity, the middle 2 min of data were selected for analysis. The length for each signal segment was 12.8 s with 1024 samples per segment. There were 4656 segments of data collected from right wrist GENEA, 4317 segments from left wrist GENEA, and 4875 segments from waist GENEA. The same periods were used for each of the three sites during validation, but the number of segments analyzed differs for each position owing to device faults. The three-dimensional data collected by GENEA (from axes *x*, *y*, and *z*) were

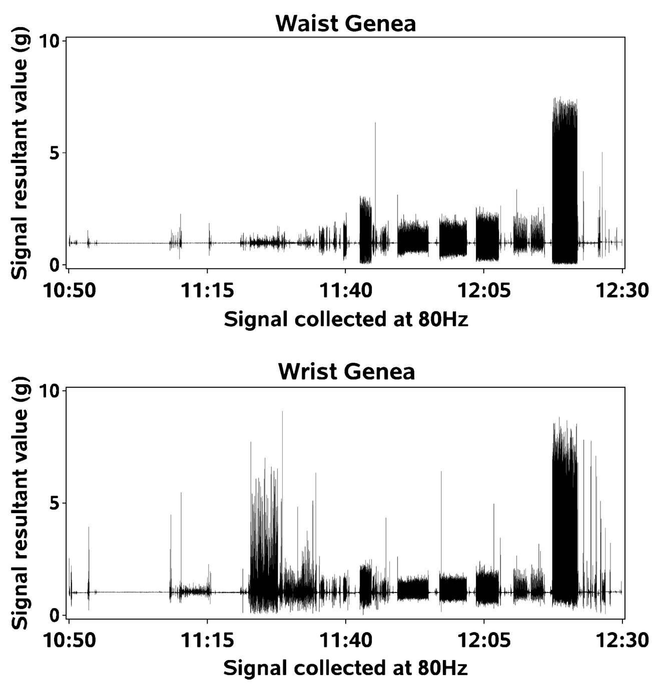

FIGURE 1—Plot of activities for participant 1 with GENEA data (*top panel*: waist-worn GENEA; *bottom panel*: wrist-worn GENEA)

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transformed into a single-dimensional signal magnitude vector (sometimes called the resultant), which is as follows:

$$\mathrm{SMV} = \sqrt{x^2 + y^2 + z^2} \quad [1]$$

Besides the mean and SD of each epoch, features from FFT and DWT were generated. For each segment, outputs from the FFT are as follows:

- f_1 — dominant frequency in each 12.8-s segment
- p_1 — power of the dominant frequency f_1
- f_2 — second dominant frequency (for wrist-worn accelerometer only)
- p_2 — power of f_2 (for wrist-worn accelerometer only)
- total power — the total power for the frequencies between 0.3 and 15 Hz
- f_{625} — dominant frequency between 0.6 and 2.5 Hz
- p_{625} — the power corresponding with f_{625}
- p_1/total power
- f_{1s}/f_{1s-1} — the ratio between dominant frequency at the current segment (f_{1s}) and the segment before (f_{1s-1})

Note that for the wrist-worn accelerometer the features "f_2" and "p_2" were introduced; these features represent the characteristics of regular hand movements for walking activities.

In addition to the features from FFT, two time domain features from DWT (32) were extracted to see whether they enhanced the classification rate.

$$\mathrm{DWT_{SMV}} = \sum_{j=\alpha}^{\beta} d_j^2 / \mathrm{SMV}^2 \quad [2]$$

$$\mathrm{DWT_{SMV1}} = \sum_{j=\alpha}^{\beta} d_j^2 / \sum_{j=1}^{J} d_j^2 \quad [3]$$

where d_j is the decomposed signal of the signal magnitude vector SMV at level $j(j = 1, \ldots, J)$. $\mathrm{DWT_{SMV}}$ represents the ratio of detail signals between levels α and β to the total power of SMV, $\mathrm{DWT_{SMV1}}$ represents the ratio of details between levels α and β to the total power of details between level 1 and J (J = 8 for this study). Wavelet "DB10" is selected as this is the closest match to walking (32), also our numerical experiments showed that for the given sampling rate of 80 Hz, the values of $\mathrm{DWT_{SMV}}$ and $\mathrm{DWT_{SMV1}}$ with $\alpha = 5$ and $\beta = 6$ are higher for walking than other activities.

Modeling and performance evaluation. Data from 16 PA tasks performed by each participant were categorized into sedentary (lying, standing, seated computer work), household (window washing, washing up, shelf stacking, sweeping), walking (4 km·h^{-1}, 5 km·h^{-1}, 6 km·h^{-1}, stairs, free-living 6-km·h^{-1} walk), and running (8 km·h^{-1}, 10 km·h^{-1}, 12 km·h^{-1}, free-living 10-km·h^{-1} run) activities using machine learning algorithms. The choice of algorithm is influenced by its recognition rate as well as by its working efficiency and interpretability. As a long-term study using streaming accelerometry will need much data processing, the efficiency of the classification algorithm is of great importance. In previous studies using pattern recognition to classify PA, various machine learning algorithms have been used, including Decision Tree (2,7), Neural Network (12), Hidden Markov Model (19,27), Support Vector Machine (34), etc. In this study, we compared the accuracy and efficiency of different machine learning algorithms to find the one most suitable for PA studies.

Before training and testing, all the features were standardized, and Support Vector Machine feature evaluation method was applied to select the feature set best for the classification (17). The following metrics were used to assess and compare the performance of the algorithms with respect to correct classification of the PA. The meanings of TP, TN, FP, FN, P, and N can be seen in Figure 2.

$$\text{FP rate} = \frac{\mathrm{FP}}{\mathrm{N}} = 1 - \text{specificity} \quad [4]$$

$$\text{TP rate} = \text{sensitivity} = \text{recall} = \frac{\mathrm{TP}}{\mathrm{P}} \quad [5]$$

$$\text{precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \quad [6]$$

$$\text{accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{P} + \mathrm{N}} \quad [7]$$

$$F - \text{score} = \frac{2}{1/\text{precision} + 1/\text{recall}} \quad [8]$$

$$\text{ROC} = \text{receiver operating characteristic} \quad [9]$$

Values for these parameters are between 0 and 1. The theoretical optimum value for FP rate is 0, and the optimum value for all the others is 1.

Performance of the models was assessed using both split-mode cross-validation (two-thirds of the samples from each activity were selected randomly for training, and the remaining one-third were used for testing) and 10-cross-validation mode (leave-one-out-cross-validation).

RESULTS

Classification using wrist data by Decision Tree. The Decision Tree J48 from WEKA software was used for the

		True class	
		p	**n**
Hypothesized class	**Y**	True positives	False positives
	N	False negatives	True negatives
Column totals:		**P**	**N**

FIGURE 2—Confusion matrix and common performance metrics.

TABLE 1. Decision Tree—classification results based on right wrist data.

Summary	
Accuracy	96.97%
Total no. instances for testing	1552 (split mode)

Detailed Accuracy by Class	TP Rate	FP Rate	Precision	Recall	*F*-Score	ROC
Sedentary	0.994	0.005	0.981	0.994	0.988	0.994
Household	0.926	0.018	0.929	0.926	0.927	0.98
Walking	0.972	0.0322	0.978	0.972	0.975	0.989
Running	1	0.001	0.987	1	0.993	0.999

Confusion Matrix
Actual Activity Class

Sedentary	Household	Walking	Running	Classified as
317	2	0	0	Sedentary
6	287	17	0	Household
0	20	753	2	Walking
0	0	0	148	Running

TABLE 3. Decision Tree—Classification results based on waist data.

Summary	
Accuracy	99.14%
Total no. instances for testing	1625 (split mode)

Detailed Accuracy by Class	TP Rate	FP Rate	Precision	Recall	*F*-Score	ROC
Sedentary	0.965	0.002	0.994	0.965	0.979	0.995
Household	0.994	0.009	0.966	0.994	0.98	0.995
Walking	1	0	1	1	1	1
Running	1	0	1	1	1	1

Confusion Matrix
Actual Activity Class

Sedentary	Household	Walking	Running	Classified as
328	12	0	0	Sedentary
2	344	0	0	Household
0	0	796	0	Walking
0	0	0	143	Running

training and classification, where the confidence was set to be 0.25 and pruning technique was applied. The features selected were f_1, p_1, f_2, p_2, total power, f_{625}, p_{625}, p_1/total power, f_{1t}/f_{1t-1}, $\mathrm{DWT_{SMV1}}$. Tables 1 and 2 show the classification results for Decision Trees based on data collected by the right and left wrist-worn GENEA, respectively, where two-thirds of the data segments were used for training and the remaining one-third for testing. The results demonstrate a high correct classification rate based on the features extracted from the streaming data. The overall accuracies are high for both right wrist GENEA data (split mode: 96.97%, κ = 0.954 ± 0.007 (SE), κ (linear weighting) = 0.969) and the left wrist GENEA data (split mode: 95.93%, κ = 0.934 ± 0.008 (SE), κ (linear weighting) = 0.957), and the values for other parameters such as FP rate, TP rate, and ROC are very close to their optimum values (0, 1, and 1, respectively). The overall accuracy by 10-cross-validation mode was 97.2% for the right wrist data and 96.01% for left wrist data (not shown in the table), similar to the split-mode accuracy. When excluding the feature $\mathrm{DWT_{SMV1}}$ from the data set during training and testing, the overall accuracy decreased slightly. For the right wrist GENEA, the accuracy was 96% for split mode and 96.7% for 10-cross-validation mode; for the left wrist GENEA, the accuracy was 95.7% for split mode and 95.8% for 10-cross-validation mode. Thus, the extra features from DWT in the time domain had little effect on the recognition rate.

Activity classification using waist data by Decision Tree. Similarly to the algorithm for wrist-worn GENEA, an algorithm based on waist data was also developed. The following features were selected using the feature selection algorithm: f_1, p_1, total power, f_{625}, p_{625}, p_1/total power, f_{1t}/f_{1t-1}, and $\mathrm{DWT_{SMV1}}$. The results of the split-mode cross-validation in Table 3 show that the PA classification algorithm for the waist-worn accelerometer performed better than the algorithms for the wrist-worn GENEA (>99% classification accuracy, κ = 0.987 ± 0.003 (SE), κ (linear weighting) = 0.991), with accuracy for classification of walking and running being 100%. The overall accuracy for the 10-cross-validation mode was 98.8%. When excluding $\mathrm{DWT_{SVM1}}$, again there was little effect on accuracy (98.95% for split-mode cross-validation and 98.7% for the 10-cross-validation mode).

Comparison of Decision Tree with other machine learning algorithms. The results from other classification algorithms are listed in Table 4 in terms of their overall accuracy and training time for the split mode. The features were standardized before training. All the algorithms used are from the open source software WEKA. For logistic regression, the ridge value for the log-likelihood was set to be $1.0e^{-8}$; for Support Vector Machine, the linear kernel was used, convergence tolerance $\varepsilon = 1.0e^{-7}$, upper bound of complexity was $c = 1.0$; for multilayer perception network, hidden layer = 5, learning rate = 0.3, and momentum = 0.2.

TABLE 2. Decision Tree—classification results based on left wrist data.

Summary	
Accuracy	95.93%
Total no. instances for testing	1439 (split mode)

Detailed Accuracy by Class	TP Rate	FP Rate	Precision	Recall	*F*-Score	ROC
Sedentary	0.979	0.004	0.985	0.979	0.982	0.994
Household	0.868	0.02	0.91	0.868	0.888	0.958
Walking	0.978	0.053	0.959	0.978	0.968	0.984
Running	1	0	1	1	1	1

Confusion Matrix
Actual Activity Class

Sedentary	Household	Walking	Running	Classified as
322	7	0	0	Sedentary
5	243	32	0	Household
0	17	745	2	Walking
0	0	0	129	Running

TABLE 4. Classification accuracy and efficiency by different algorithms.

	Overall Accuracy (%)			Time Taken in Training (s)		
Algorithm	Left Wrist	Right Wrist	Waist	Left Wrist	Right Wrist	Waist
Decision Tree	95.93	96.97	99.14	0.23	0.19	0.05
Naive Bayes	95.33	95.26	98.21	0.05	0.02	0.01
Logistic regression	95.73	95.65	99.4	12.07	1.61	4.46
Support Vector Machine	96.4	96.76	99.3	4.89	3.97	1.61
Neural Network	95.93	96.76	99.6	373	294	174

The results show that almost all the algorithms have satisfactory classification results with the Decision Tree and the Support Vector Machine having the highest accuracy.

DISCUSSION

The main objective of this study was to design algorithms suitable for PA monitoring using a wrist-worn accelerometry device. Various features were extracted from the original data via signal processing to distinguish walking, running, household, and sedentary activities. The results show that the algorithms developed in this study can classify different activities efficiently with high accuracy using a wrist-worn accelerometer. This may lead to an improvement over the conventional cut point method that relies on a single feature (root mean or average) from each user-defined epoch and can lead to misclassification of activities with similar energy expenditure but different counts or similar counts but different energy expenditure (27).

Different machine learning algorithms were tested for PA classification. All algorithms produced a satisfactory recognition rate, proving that the features generated from the data were appropriate and robust. The highest accuracy was shown by the Support Vector Machine and the Decision Tree. However, as a function-based algorithm, the Support Vector Machine normally takes a longer time than the Decision Tree for classification; thus, considering both efficiency and accuracy, the Decision Tree approach was considered the optimal application for PA classification.

The performance of algorithms based on the wrist-worn GENEA was also compared with that of algorithms based on the GENEA worn at the waist. There are a lot of movements from limbs during general everyday activities, which increase the difficulty of classification when the data are collected from a wrist-worn monitor. Thus, the algorithms based on the waist-worn GENEA had slightly better results (98.2%–99.1%) than algorithms based on the right wrist-worn GENEA (95.3%–97%) or the left wrist-worn GENEA (95.3%–96.4%). However, the algorithms based on wrist-worn GENEA are robust enough for daily PA monitoring, with the right wrist-worn GENEA being a better choice.

Classification of activity type, and thus improved estimation of energy expenditure, has previously been achieved with some success using accelerometer data, collected from a monitor worn at the waist, in 1-s or 10-s epochs in a laboratory setting. Crouter et al. (11) used the variability between ActiGraph counts collected in successive 10-s epochs to distinguish walking and running from lifestyle activities. More sophisticated pattern recognition approaches have also been used. For example, Pober et al. (27) compared quadratic discriminate analysis and a hidden Markov model to classify four activity types (working at a computer, walking, walking uphill, vacuuming) from ActiGraph counts collected in 1-s epochs. Both methods improved estimation of activity intensity relative to the cut point approach and reduced the misclassification of activities with similar EE, but different counts, and activities with similar counts, but different EE.

More recently, using artificial neural networks based on the distribution of ActiGraph counts within a 1-min segment, Staudenmayer et al. (33) were able to classify a range of controlled laboratory activities with an accuracy of 88.8%. De Vries et al. (12) used a similar approach but also considered an ActiGraph worn at the ankle. The waist-worn ActiGraph correctly classified the five activities (sitting, standing, stairs, walking, cycling) 80.4% of the time; and the ankle-mounted ActiGraph, 77.7% of the time. However, as these approaches rely on accelerometer data collected in epochs, they require an activity to be undertaken continuously for 1 min to be classified. This is frequently not the case in free-living individuals and the ability to be able to classify activities from shorter segments of time as in the current study is desirable.

This has been done previously with a waist-mounted triaxial accelerometer. Using a decision tree approach, Bonomi et al. (7) classified 93% of activity types (lying, sitting, standing, dynamic standing, walking, running, and cycling) with a triaxial accelerometer mounted on the lower back collecting data at 20 Hz. As in the current study, 12.8-s segments were used. The authors reported that segment size could be reduced to 6.4 s, although no lower, without compromising classification accuracy. The lower accuracy, relative to the current study, reported by Bonomi et al. may be related to the greater number of activity types classified and/or the lower frequency of data collection. Also using a waist-mounted triaxial accelerometer (sampling at 32 Hz), Oshima et al. (26) reported a similar classification accuracy to the current study (98.7% cf., >99%) across 12 activity types. The optimal classification approach reported by the authors examined the ratio of unfiltered to filtered acceleration of 10-s segments, to consider the ratio of dynamic to gravitational acceleration.

An important advance of the current study is the ability to classify activities from a wrist-worn monitor. Further, with the exception of the study of Oshima et al. (26), the classification accuracy for the GENEA worn at the wrist was greater than the classification accuracy for waist-worn monitors used in previous studies. This is important because wearing an accelerometer on a belt round the waist, or on a belt clip, can contribute to low compliance because it necessitates removal when changing clothes, sleeping and participating in some activities; for example, contact sports, formal occasions (15). Further, they are not waterproof, requiring participants to remove the monitor when there is a risk of it getting wet. The resulting loss of data can be extensive. For example, in the National Health and Nutrition Examination Survey in the United States (2003–2004), only 26% of the sample had seven valid days of accelerometer wear (35). Our pilot work has indicated that, relative to a standard waist-worn monitor, a wrist-worn monitor is more acceptable to participants and compliance is improved.

In addition to the loss of data due to low compliance, nonwear leads to analytical problems when determining whether a string of zero counts is a result of time spent sedentary or whether the device has been removed (10,15,24,31). This is an important question because if the person has been sedentary and the data are misclassified as monitor removal, sedentary time will be underestimated and mean activity level may be overestimated. Alternatively, if the person has removed the monitor and engaged in some activity and this is misclassified as sedentary time, then sedentary time will be overestimated and mean activity level will be underestimated (10,31). With the current increasing public health focus on sedentary time (1), this question is particularly pertinent.

In contrast to the earlier studies focusing on classifying activities, this study did not aim to classify specific types of household activities or postures. It is possible this contributed to the greater classification accuracy shown in the current study. The walking category (including stairs) reflected activities of a moderate intensity (14); the running category, activities of a vigorous intensity (14); and the sedentary category, sitting, standing, and lying (with no attempt to differentiate between posture). The lack of posture differentiation is a limitation because this may be important for investigating health outcomes specific to sitting time. Further, the household activity contained activities that would be classed as light intensity, but also activities that would be classed as moderate intensity (14); further research will aim to separate out light- and moderate-intensity household activities. However, when wearing the GENEA on the right wrist, walking, and running (the dominant moderate and vigorous activities in most adults) were correctly identified >97.8% of times. Sedentary activities were correctly identified 98.1% of the time. As in the earlier research, the greatest misclassification was between household activities and walking with household activities being correctly identified 92.9% of the time. Finally, we recognize that the generalizability of the model generated may be limited by the use of the same monitors in the same locations for each participant. However, the intermonitor variability of the GENEA is low (CV_{inter} = 2.1%, (14)) and lower than that reported for other accelerometers, e.g., ActiGraph.

In conclusion, the GENEA, whether worn at the wrist or the waist, shows high accuracy for classification of sedentary activities, household activities, walking, and running. The validity of the GENEA worn at the wrist is particularly encouraging because there is potential for greater compliance to activity monitoring protocols. Further research is needed to distinguish between light and moderate household activities and test how well these algorithms perform in a free-living setting when activity is sporadic, is unstructured, and contains activity transitions. Further research should also consider the optimal sampling frequency for activity classification. If the same classification accuracy can be achieved with a lower sampling frequency, this will prolong the period of use of the accelerometer on a single battery charge and reduce the processing time and power required to detect and classify activity.

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