Activity Classification Using the GENEA: Optimum Sampling Frequency and Number of Axes

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ABSTRACT

ZHANG, S., P. MURRAY, R. ZILLMER, R. G. ESTON, M. CATT, and A. V. ROWLANDS. Activity Classification Using the GENEA: Optimum Sampling Frequency and Number of Axes. *Med. Sci. Sports Exerc.*, Vol. 44, No. 11, pp. 2228–2234, 2012. **Introduction**: The GENEA shows high accuracy for classification of sedentary, household, walking, and running activities when sampling at 80 Hz on three axes. It is not known whether it is possible to decrease this sampling frequency and/or the number of axes without detriment to classification accuracy. The purpose of this study was to compare the classification rate of activities on the basis of data from a single axis, two axes, and three axes, with sampling rates ranging from 5 to 80 Hz. **Methods**: Sixty participants (age, 49.4 yr (6.5 yr); BMI, 24.6 kg·m^{-2} (3.4 kg·m^{-2})) completed 10–12 semistructured activities in the laboratory and outdoor environment while wearing a GENEA accelerometer on the right wrist. We analyzed data from single axis, dual axes, and three axes at sampling rates of 5, 10, 20, 40, and 80 Hz. Mathematical models based on features extracted from mean, SD, fast Fourier transform, and wavelet decomposition were built, which combined one of the numbers of axes with one of the sampling rates to classify activities into sedentary, household, walking, and running. **Results**: Classification accuracy was high irrespective of the number of axes for data collected at 80 Hz (96.93% ± 0.97%), 40 Hz (97.4% ± 0.73%), 20 Hz (96.86% ± 1.12%), and 10 Hz (97.01% ± 1.01%) but dropped for data collected at 5 Hz (94.98% ± 1.36%). **Conclusion**: Sampling frequencies >10 Hz and/or more than one axis of measurement were not associated with greater classification accuracy. Lower sampling rates and measurement of a single axis would result in a lower data load, longer battery life, and higher efficiency of data processing. Further research should investigate whether a lower sampling rate and a single axis affects classification accuracy when considering a wider range of activities. **Key Words:** ACCELEROMETER, WRIST WORN, WALKING, FAST FOURIER TRANSFORM, MACHINE LEARNING

Daily physical activity is positively associated with health status and quality of life (7,9,10). Accurate measurement of physical activity is necessary to identify dose–response relationships between activity and health outcomes and the differential effect of different types of physical activity on different health outcomes (10). Accelerometry has become the method of choice for the measurement of habitual physical activity (16,17). However, accelerometry is not without limitations; two of the main limitations relate to compliance and misclassification of activity intensity. Both these limitations are currently being addressed. For example, wrist-worn devices lead to greater compliance than the more typical waist-worn devices (18), and there is increasing evidence for their validity (5,18,19). Furthermore, there is increasing research into classification of activity type, which can help address misclassification of intensity (2,3,12,13,15,19).

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Several previous studies have classified physical activity type using accelerometry devices (2–4,6,8,12,13,15,19). Classification studies have used accelerometers with a variety of specifications including single, two, or three axes and with data resolutions ranging from 10-s epochs to raw acceleration data sampled between 10 and 160 Hz. However, we are not aware of a study that compares the accuracy of classification across different accelerometer specifications. The number of sensors and the sampling rate are closely associated with the size and performance (e.g., data storage and processing capacity, reliability of monitoring, and battery life) of the device. Thus, a clear understanding of the sampling frequency and number of axes required, whereas still retaining useful information in the data, can help us to optimize the functionality of the accelerometry device.

We have previously shown that the GENEA accelerometer shows high accuracy for classification of sedentary, household, walking, and running activities when sampling at 80 Hz on three axes. Furthermore, classification accuracy at the wrist was high and only slightly lower than that at the waist, indicating that the wrist site is a valid option for assessment of habitual physical activity (5,19). It is not known whether it is possible to decrease this sampling rate and/or the number of axes without detriment to classification accuracy.

The aim of this study was to determine whether reduced axes and sampling still provide acceptable classification. To do this, we compared the classification accuracy of physical activities from a series of algorithms developed with data collected at 80 Hz from a single axis, two axes, and three axes and with the raw data down-sampled to rates ranging from 5 to 40 Hz. The GENEA was worn at the wrist because this site has been shown to be valid (5,19) and to maximize compliance during assessment of habitual activity (18).

METHODS

Participants

Sixty 40- to 65-yr-old volunteers, 23 males (age, 48.9 yr (6.8 yr); BMI, 25.9 kg·m^{-2} (2.7 kg·m^{-2})) and 37 females (age, 49.6 yr (6.4 yr); BMI, 23.8 kg·m^{-2} (3.5 kg·m^{-2})), were recruited for the study. Fifty-five participants were right handed and five were left handed. All participants were free from musculoskeletal injury and diagnosed disease and had no affirmative answers to the Physical Activity Readiness Questionnaire. The study was approved by the ethics committee of the School of Sport and Health Sciences at the University of Exeter, and all participants gave written informed consent.

Data Collection

Each participant completed an ordered series of 10–12 semistructured activities in the laboratory and outdoor environment. The activities were lying, standing, seated computer work, 4 km·h^{-1} walk, 5 km·h^{-1} walk, 6 km·h^{-1} walk, walking up and down stairs, free-living 6 km·h^{-1} walk, two household activities (randomly selected from window washing, washing up, shelf stacking, and sweeping), one run (8 km·h^{-1}, 10 km·h^{-1} or 12 km·h^{-1} run), and an optional free-living 10 km·h^{-1} run. All activities were performed for around 4.5 min, except lying, which was performed for 10 min. Each participant wore one GENEA on their right wrist, with the sampling rate set at 80 Hz for three axes.

GENEA

The GENEA is a triaxial acceleration sensor developed by Unilever Discover (Colworth, United Kingdom) and manufactured and distributed by ActivInsights Ltd. as the GeneActiv (www.geneactiv.co.uk; Kimbolton, Cambridgeshire, United Kingdom). It is a triaxial ±6*g* seismic acceleration sensor housed in a small (36 × 30 × 12 mm) light weight (16 g) casing with a splash proof design (Fig. 1). The sampling rate of the GENEA can be selected by the user and ranges from 10 to 160 Hz. The reliability and validity of the GENEA, when data are integrated into epochs, are comparable with the ActiGraph (5). The raw acceleration data shows high accuracy for classification of sedentary activities, household activities, walking, and running when sampling at 80 Hz on three axes (19). Note that the commercially available GeneActiv is waterproof and has a ±8*g* seismic acceleration sensor and a sampling range of 10–100 Hz.

Data Extraction

To address the objectives of this study, first of all, data sets from one, two, or three axes (uniaxial, biaxial, triaxial) were generated from the original 80-Hz wrist-worn GENEA data with all possible combinations, including *x*, *y*, *z* for uniaxial cases, *xy*, *xz*, *yz* for biaxial cases, and *xyz* for triaxial case, respectively.

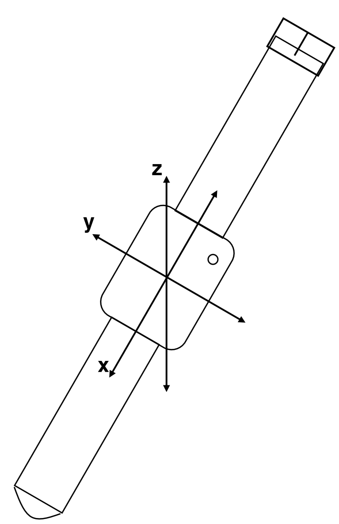

FIGURE 1—GENEA with *x*, *y*, and *z* axes labeled.

Triaxial data. The three-dimensional data were transformed into a single-dimensional signal magnitude vector (SVM, sometimes called the resultant):

$$\mathrm{SVM}_{xyz} = \sqrt{x^2 + y^2 + z^2} \qquad [1]$$

Biaxial data. Data from the x and y axes, x and z axes, and y and z axes (Fig. 1) were used. When wearing the GENEA on the wrist, the x and y axes normally capture forward/backward and upward/downward motions. The two-dimensional data were transformed into a single-dimensional signal magnitude vector:

$$\mathrm{SVM}_{xy} = \sqrt{y^2 + z^2} \qquad [2]$$

$$\mathrm{SVM}_{xz} = \sqrt{y^2 + z^2} \qquad [3]$$

$$\mathrm{SVM}_{xz} = \sqrt{x^2 + z^2} \qquad [4]$$

Uniaxial data. Data from the x axis, y axis, and z axis (Fig. 1) were used. With the GENEA worn on the wrist, y axis is in line with the arm and normally captures forward/backward motion. The data were transformed into its absolute value vector:

$$\mathrm{SVM}_x = |x| \qquad [5]$$

$$\mathrm{SVM}_y = |y| \qquad [6]$$

$$\mathrm{SVM}_z = |z| \qquad [7]$$

In addition, data sets corresponding to five different sampling rates (5, 10, 20, 40, and 80 Hz) were generated. To cover a wide frequency range, we choose to halve the frequency at each step, and data corresponding to the different sampling rates were extracted as follows:

- 80 Hz: Original data collected
- 40 Hz: The first sample in every two was selected from the original data
- 20 Hz: The first sample in every four was selected from the original data
- 10 Hz: The first sample in every eight was selected from the original data
- 5 Hz: The first sample in every 16 was selected from the original data

Feature extraction. For each activity, the middle 2-min data were selected for analysis. The length for each signal segment was set as 12.8 s. Besides the average and SD values, fast Fourier transform and wavelet decomposition were applied on each successive 12.8-s data (SVM_{xyz}, SVM_{xy}, SVM_y, etc.) to generate features. The data and the features used in this study were similar to those described in our earlier study (19). After data processing and feature extraction, each data set was split into 5535 episodes, with each episode representing 12.8-s data for one of the 16 activities. A feature vector was generated from each episode, including the following:

- average—the average value for each 12.8-s segment
- deviation—the SD value for each segment
- f_1—dominant frequency in each 12.8-s segment
- p_1—power of the dominant frequency f_1
- f_2—second dominant frequency
- p_2—power of f_2
- total power—the total power for the frequencies between 0.3 and 15 Hz (0.3–2.5 Hz for 5-Hz sampling, 0.3–5 Hz for 10-Hz sampling, 0.3–10 Hz for 20-Hz sampling, 0.3–15 Hz for 40- and 80-Hz sampling)
- f_{625}—dominant frequency between 0.6 and 2.5 Hz
- p_{625}—the power corresponding with f625
- p_1/total power
- f_{1s}/f_{1s-1}—the ratio between dominant frequency at the current segment (f_{1s}) and the segment before ($f_{1s\text{-}1}$)
- Feature from wavelet decomposition: $\mathrm{DWT_{SVM}} = \sum_{j=\alpha}^{\beta} d_j^2 / \mathrm{SVM}^2$

where d_j is the decomposed signal of the signal magnitude vector SVM at level $j (j = 1, \ldots, J)$. $\mathrm{DWT_{SVM}}$ represents the ratio of detail signals between level α and β to the total power of SVM. Wavelet "DB10" is selected in this study with $J = 8$. For data sampled at 80 Hz, $\alpha = 5$, $\beta = 6$; for data sampled at 40 Hz, $\alpha = 4$, $\beta = 5$; for data sampled at 20 Hz, $\alpha = 3$, $\beta = 4$; for data sampled at 10 and 5 Hz, $\alpha = 2$, $\beta = 3$.

Modeling. We attempted to classify the 16 physical activity tasks into four groups: sedentary (consistent with lying, standing, and seated computer work), household (window washing, washing up, shelf stacking, and sweeping), walking (4, 5, and 6 km·h^{-1}, stairs, and free-living 6 km·h^{-1} walk), and running (8, 10, and 12 km·h^{-1} and free-living 10 km·h^{-1} run) activities using machine learning algorithms. Success was measured by the proportion of correct classifications by each method. Logistic regression, decision tree, and support vector machine classifiers were used for investigation; all the algorithms used are from the open-source software WEKA. The parameters for decision tree and support vector machine used in this study are the same as in our former study (19) and were fixed for all the training and tests. For Bayesian belief network, the structure searching method was the "Tabu Search" with the maximum number of parents node to be 2, and the estimator was selected to be "Simple-Estimation" with $\alpha = 0.5$. For the training and test, 10-cross-validation mode and the split mode cross-validation method were applied to assess performance. For the split mode, 2/3 of the samples from each activity were selected randomly for training, and the remaining 1/3 samples were used for testing. Before training and testing, all the features were standardized.

RESULTS

Table 1 shows the classification results from different algorithms for all the possible combinations of axes at the

TABLE 1. Classification results for three axes (*x*, *y*, and *z*), different combinations of two axes (*x* and *y*, *x* and *z*, *y* and *z*), and single axes (*x*, *y*, or *z*) for data collected at 80 Hz.

		Logistic Regression	Decision Tree	Support Vector Machine	Bayesian Network
xyz	Incorrect classification rate (%)	2.76	2.71	2.71	4.44
	Kappa statistic	0.953	0.954	0.954	0.926
	Root mean square error	0.1	0.114	0.315	0.137
xy	Incorrect classification rate (%)	1.83	1.50	1.57	3.66
	Kappa statistic	0.972	0.977	0.976	0.945
	Root mean square error	0.084	0.086	0.314	0.122
xz	Incorrect classification rate (%)	2.22	1.37	2.22	3.0
	Kappa statistic	0.966	0.979	0.966	0.955
	Root mean square error	0.094	0.083	0.315	0.115
yz	Incorrect classification rate (%)	2.35	2.67	2.15	4.51
	Kappa statistic	0.964	0.959	0.967	0.932
	Root mean square error	0.096	0.111	0.315	0.139
x	Incorrect classification rate (%)	4.77	6.01	3.73	7.91
	Kappa statistic	0.928	0.909	0.944	0.882
	Root mean square error	0.138	0.166	0.317	0.18
y	Incorrect classification rate (%)	2.55	2.75	2.35	3.33
	Kappa statistic	0.961	0.958	0.964	0.95
	Root mean square error	0.098	0.114	0.315	0.125
z	Incorrect classification rate (%)	5.62	5.62	3.20	6.34
	Kappa statistic	0.915	0.915	0.951	0.904
	Root mean square error	0.152	0.163	0.316	0.165

original sampling rate of 80 Hz. The results from each algorithm are the averaged accuracy from 10 cross-validations. Across all algorithms, the accuracies were 96.85% ± 0.86% (mean ± SD) for triaxial. The accuracies from biaxial cases were similar, regardless of axis combination: "*xy*" = 97.86% ± 1.02%; "*xz*" = 97.8% ± 0.67%; and "*yz*" = 97.16% ± 1.11%. For uniaxial cases, the results from "*y*" (97.26% ± 0.42%) were the best, with the cases of "*x*" (94.4% ± 1.8%), and "*z*" (94.8% ± 1.37%) a bit lower. Classification results were highest for support vector machine (97.44% ± 0.72%), similar for logistic regression (96.84% ± 1.44%) and decision tree (96.81% ± 1.88%), but lower for the Bayesian network (95.26% ± 1.78%).

Tables 2 to 4 and Figure 2 show the classification results from logistic regression, decision tree, and support vector machine in terms of the different sampling rates. The results from triaxial, biaxial and uniaxial combinations were illustrated, including the cases of "*xyz*," "*xy*," and "*y*," respectively. To ease the computation load, all results in Tables 2 to 4 were obtained from the split mode, where 2/3 of the samples were used for training and the remaining 1/3 for test. Across all algorithms and axis numbers, models using data collected at 80 Hz (97.43% ± 0.4% (mean ± SD)), 40 Hz (97.63% ± 0.53%), 20 Hz (97.25% ± 0.58%), and 10 Hz (97.43% ± 0.44%) performed well, with classification accuracy consistently greater than 96.3% (Fig. 2). Kappa values and error were also similar within algorithm when sampling rate was 10 Hz or greater (Tables 2–4). Classification accuracy dropped for data sampled at 5 Hz (95.22% ± 1.13%), with corresponding decreases in kappa and increased error rates (Fig. 2, Tables 1–3). Models based on uniaxial (*y*) (97.13% ± 1.15%), biaxial (*xy*) (97.11% ± 0.78%), and triaxial (96.73% ± 1.34%) data showed similar classification results (Fig. 2, Tables 2–4).

DISCUSSION

The results of this study indicate that the accuracy of classification of activities into four categories (sedentary, household, walking, and running) was not compromised when sampling rate was decreased from 80 to 10 Hz, and the number of axes of measurement was decreased from three to one. This is significant because a reduction in the number of sensors required and/or sampling rate could translate into an improved performance of the monitor, as defined by memory capacity, battery life, and processing speed, for a given size. In this study, only the data sets corresponding to 80 Hz

TABLE 2. Classification results using decision tree.

	Incorrectly Classified Rate (%)	Kappa Statistic	Mean Absolute Error	Root Mean Square Error
Triaxial (*x*, *y*, *z*)				
80 Hz	2.71	0.9543	0.0158	0.1137
40 Hz	1.79	0.9699	0.0108	0.0913
20 Hz	2.38	0.9598	0.015	0.1071
10 Hz	2.01	0.9662	0.0135	0.0966
5 Hz	4.55	0.9229	0.0284	0.1452
Biaxial (*x*, *y*)				
80 Hz	3.09	0.9478	0.016	0.1181
40 Hz	2.11	0.9644	0.0121	0.1006
20 Hz	2.60	0.9563	0.0153	0.1122
10 Hz	2.33	0.9606	0.0139	0.1027
5 Hz	3.79	0.9356	0.024	0.1347
Uniaxial (*y*)				
80 Hz	1.84	0.9689	0.0117	0.093
40 Hz	2.11	0.9644	0.0136	0.0983
20 Hz	1.79	0.9698	0.0112	0.0904
10 Hz	2.11	0.9643	0.0128	0.1002
5 Hz	3.47	0.9416	0.0196	0.1284

TABLE 3. Classification results using support vector machine.

	Incorrectly Classified Rate (%)	Kappa Statistic	Mean Absolute Error	Root Mean Square Error
Triaxial (*x*, *y*, *z*)				
80 Hz	2.71	0.9544	0.2523	0.3154
40 Hz	2.17	0.9637	0.2519	0.3148
20 Hz	3.36	0.9436	0.2528	0.3163
10 Hz	3.14	0.9472	0.2528	0.3163
5 Hz	6.12	0.8962	0.256	0.3212
Biaxial (*x*, *y*)				
80 Hz	2.55	0.957	0.2523	0.3154
40 Hz	2.06	0.9654	0.252	0.3149
20 Hz	2.55	0.9571	0.2524	0.3156
10 Hz	2.44	0.9589	0.2523	0.3154
5 Hz	4.17	0.929	0.2541	0.3183
Uniaxial (*y*)				
80 Hz	2.01	0.9662	0.2519	0.3147
40 Hz	2.76	0.9532	0.2525	0.3155
20 Hz	2.38	0.9599	0.2522	0.3152
10 Hz	2.28	0.9617	0.252	0.3149
5 Hz	3.69	0.9379	0.2538	0.3177

were directly collected from the GENEA; all other data sets were generated by using lower resolution data from one, two, or all three of the axes. This method of down sampling is consistent with the sampling mechanism of the accelerometer and ensures that all data sets correspond exactly.

The general rule for choosing the sampling rate is given by the Nyquist sampling theorem (11): the sampling rate *must* be at least two times the upper limit, f_u, of the frequency range of interest; otherwise, the signal will be distorted and information will be lost. However, any high-frequency noise content that happens to be present in the signal will be mapped to the frequency range of interest—this is known as aliasing. A strategy to suppress the noise effect is to first sample at higher frequencies, then apply a low-pass filter (or similar) to remove the noise. The cut-off of the filter should be set at f_u to minimize aliasing when the signal is down-sampled at a later stage. For the physical activities included in this study, most of the dominant frequencies are lower than 3.5 Hz. Sampling rates between 10 and 80 Hz resulted in similar classification accuracy. However, in line with the Nyquist limit, the data set generated at 5 Hz had a lower recognition rate.

TABLE 4. Classification results using logistic regression.

	Incorrectly Classified Rate (%)	Kappa Statistic	Mean Absolute Error	Root Mean Square Error
Triaxial (*x*, *y*, *z*)				
80 Hz	2.76	0.953	0.024	0.1
40 Hz	2.44	0.959	0.02	0.1
20 Hz	3.69	0.938	0.029	0.115
10 Hz	3.09	0.948	0.026	0.11
5 Hz	6.08	0.895	0.046	0.151
Biaxial (*x*, *y*)				
80 Hz	2.71	0.954	0.022	0.1
40 Hz	2.33	0.961	0.019	0.095
20 Hz	3.14	0.947	0.025	0.111
10 Hz	2.66	0.955	0.022	0.101
5 Hz	4.77	0.919	0.035	0.13
Uniaxial (*y*)				
80 Hz	2.76	0.953	0.024	0.101
40 Hz	3.58	0.939	0.029	0.119
20 Hz	2.82	0.953	0.024	0.103
10 Hz	3.09	0.948	0.026	0.11
5 Hz	6.34	0.893	0.048	0.155

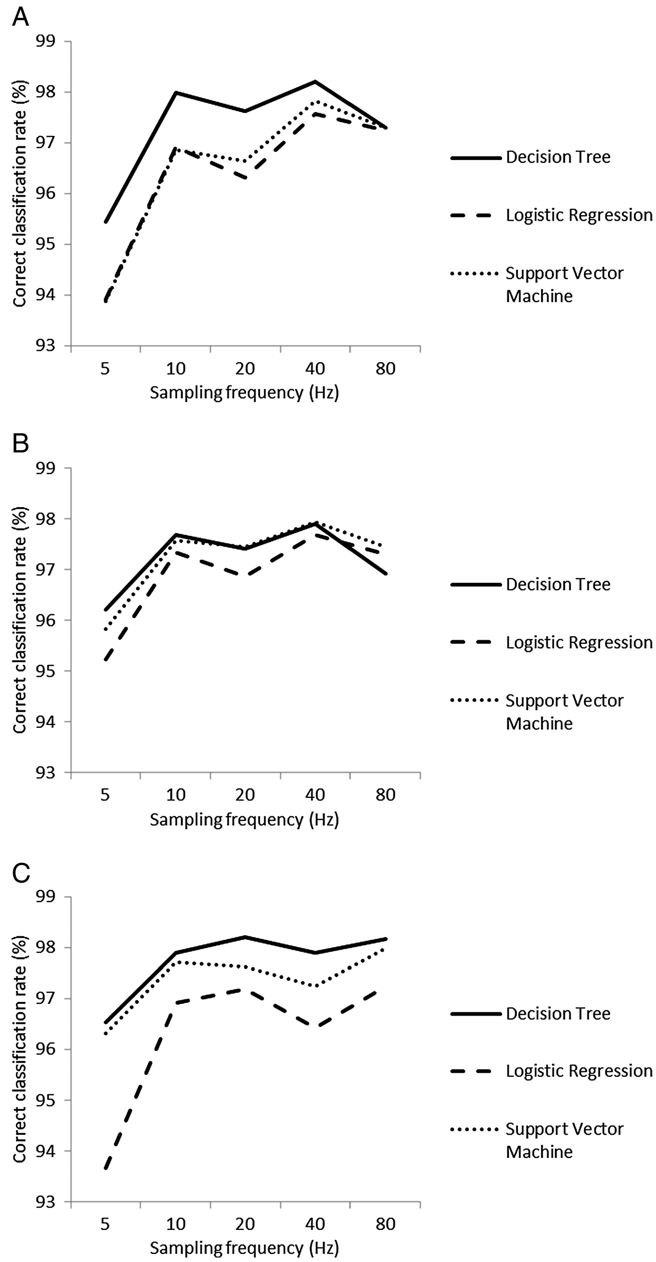

FIGURE 2—Recognition rate in terms of GENEA sampling rate and algorithm for three axes (*x*, *y*, and *z*) (A), two axes (*x* and *y*) (B), and one axis (*y*) (C).

The algorithms used in this study showed no advantage, in terms of classification accuracy, of three axes over two axes or a single axis. In contrast, the uniaxial and biaxial data sets were associated with slightly better classification performance. The nature of the data processing may have masked any possible advantages of multiple axes. Specifically, multiple axial data were transferred into a single value (SVM) before generation of features. Second, the features used in this study were mainly related to the frequency distribution of accelerations during different activities; information from one or two axes may be enough to catch these frequency characteristics. Finally, for the purpose of classifying 16 physical activities into four broad categories, rather than individual activities or finer categories, the information from multiple axes and higher resolution may be superfluous. High sample frequency may become more important when discriminating different activity types that are of similar intensity level (walking vs. stair walking, sitting vs. standing, etc).

Bonomi et al. (2) used features from acceleration signals sampled at 20 Hz from three axes separately from an accelerometer positioned at the lower back. They reported a classification accuracy of 93% for segments of activity 6.4 or 12.8 s, although accuracy dropped if the segment length was reduced further. The lower accuracy relative to the current study is probably due to categorization of activities into finer categories including individual postures. Whether the classification accuracy would have been reduced by collapsing of the triaxial signals into a composite value was not tested. Oshima et al. (12) categorized activity using the ratio of filtered vertical acceleration to filtered horizontal acceleration from an accelerometer worn on a waist belt. Accuracy ranged from 63.6% to 95.5% and was lower than accuracy using the ratio of unfiltered to filtered total acceleration (95.5%–100%). Because of the differences in modeling approaches, accelerometer wear site, activities, and classification categories, it is difficult to draw any conclusions regarding potential advantages of features from separate axes over a composite multiaxial measure.

In the present study, we selected a 12.8-s window for activity classification and did not consider different window sizes. The effect of window size on classification accuracy is of interest, both from the perspective of encompassing sufficient data to characterize a particular activity class, the likelihood and consequences of activity transitions within any window period and also regarding the interaction of the window length with sensor number and sampling characteristics. This has implications for hardware, computational efficiency and latency as well as power requirement consequences. The aim of this study was to determine whether reduced sampling and axes still provide acceptable classification under the same conditions and physical activity classes as our earlier study with triaxial 80-Hz data (19); thus, it was necessary to fix the window size to 12.8 s, and exploration of the effects of reducing window size was beyond the scope of this article. Alternate future approaches could include nonuniform sampling strategies that dynamically adjust to the incoming data characteristics (e.g., increase sampling frequency on detection of movement, reduce sampling frequency to a level sufficient to detect a further transition of activity type), effects of alternative window durations, and other data segmentation approaches.

The choice of sampling rate and number of accelerometer axes of measurement to be used should depend on the research question. For example, for tremor and balance studies, a high sampling rate is needed to capture the frequency of interest and reduce the effect of background noise or of peaks resulting from sudden voluntary or involuntary movements (1,14). However, if the aim is to classify daily activities, a sampling frequency of 10–20 Hz may be sufficient. Further research is needed to investigate whether three axes results in improved classification when using algorithms that focus on individual axis measurements and when classifying activities into finer categories.

In conclusion, when using the wrist-worn GENEA, high accuracy for classification of sedentary activities, household activities, walking, and running can be achieved using data sampled at 10–20 Hz on a single axis, capturing forward/backward motion. This is an important finding because a lower sampling rate combined with fewer axes of measurement in the monitor would 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. In addition, to reduced data size, if fewer accelerometer chips are contained in the monitor, it would be possible to either reduce the weight and size or leave more space to improve/add other functions. For example, some participants wearing the GENEA on their wrist have expressed the desire for a functional watch face on the monitor. Such an addition may improve compliance and acceptability of the monitor, making it more suitable for everyday physical activity monitoring and lifestyle intervention.

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The results of the present study do not constitute endorsement by the authors or the American College of Sports Medicine of the products described in this article.

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