Accelerometer-Based MET Estimation for Wearable Energy Expenditure Monitoring

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Abstract: Accurately estimating energy expenditure (EE) from wearable devices remains challenging without heart-rate sensing or indirect calorimetry. This work investigates a lightweight, accelerometer-based framework for estimating metabolic equivalent (MET) intensity levels using only wrist- and hip-mounted triaxial accelerometers. We extract ENMO-derived features and apply published nonlinear mappings to estimate MET values without user calibration, multi-sensor fusion, or physiological measurements. To assess the plausibility of these estimates in the absence of calorimetric ground truth, we introduce an indirect validation strategy based on three criteria: (1) consistency with benchmark MET tables, (2) cross-subject stability, and (3) correct intensity ordering across walking, jogging, and stair-related activities. Results show that accelerometer-only MET estimation captures expected physiological patterns and separates activity types in a realistic and interpretable manner. These findings highlight the potential of ENMO-based methods for real-time wearable EE monitoring, particularly in applications where relative intensity tracking is more important than precise caloric accuracy.

1 INTRODUCTION

Energy expenditure (EE) is a fundamental physiological quantity used in biomedical monitoring, physical activity assessment, and wearable-based health analytics. Gold standard EE measurement relies on indirect calorimetry or the combination of motion sensing with heart-rate–derived metabolic equations. Although accurate, these approaches require specialized equipment, controlled laboratory conditions, or multi-sensor configurations that limit scalability in real-world settings (Delsoglio et al., 2019; Chen et al., 2020). As modern wearable devices routinely incorporate high-resolution accelerometers, there is increasing interest in methods that estimate EE using only inertial signals.

Prior work has established relationships between accelerometer-derived features and metabolic equivalent (MET) values. In this paper, we do not aim to recover laboratory-grade energy expenditure (EE) (e.g., calorimetry-level kilocalories). Instead, we use MET units as a standardized *intensity proxy* to summarize movement into broad zones (light/moderate/vigorous) in a way that is interpretable and compatible with mobile deployment. This focus is particularly relevant when heart-rate sensing is unavailable (e.g., smartphone-only sensing), unreliable under motion and poor skin contact, undesirable for privacy reasons, or impractical for always-on low-power operation. In such settings, an accelerometer-only MET proxy can provide useful, real-time intensity feedback without requiring physiological sensors or individualized calibration.

This work investigates a lightweight, accelerometer only framework for estimating MET-based EE levels using wrist- and hip-mounted triaxial accelerometers. We compute ENMO (Euclidean Norm Minus One) features and apply published nonlinear mappings to derive MET estimates without using heart-rate data or calorimetric labels. Because our dataset does not include physiological ground truth, we introduce an indirect validation strategy that evaluates whether predicted MET patterns match established intensity relationships across activities and align with published benchmark MET tables.

The contributions of this work are:

- A practical, accelerometer-only pipeline for estimating MET-based EE suitable for embedded and mobile deployment.
- An indirect validation framework based on activity-specific MET distributions, cross-subject stability, and expected intensity ordering, en-

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abling evaluation in the absence of calorimetry.

- An empirical analysis using wrist and hip-mounted accelerometer data collected across multiple controlled locomotor activities, including walking, jogging, and stair navigation.
- A discussion of how lightweight MET estimation can support wearable EE monitoring and real-time intensity feedback in mobile systems.

By focusing on relative intensity patterns rather than precise caloric output, this work aims to provide a deployable EE estimation method that leverages commodity accelerometers and supports a wide range of wearable and biomedical applications.

2 BACKGROUND AND RELATED WORK

2.1 Energy Expenditure Estimation from Wearable Sensors

Energy expenditure (EE) is commonly measured using indirect calorimetry or heart-rate–based metabolic equations, which offer high accuracy but require specialized equipment (Delsoglio et al., 2019; Chen et al., 2020). For mobile and wearable applications, accelerometer-only EE estimation has become an attractive alternative. Classical approaches convert accelerometer counts into Metabolic Equivalent of Task (MET) values through regression or nonlinear mappings (Lyden et al., 2010). More recent approaches operate directly on raw accelerometer signals using features such as ENMO, signal magnitude area, and window-level statistics to approximate METs or activity intensity (Bakrania et al., 2016; Dehkordi et al., 2020). Although these methods sacrifice clinical precision, they produce physiologically meaningful relative-intensity patterns suitable for real-world deployment.

A recurring theme across this work is the tradeoff between physiological accuracy and practical deployability. Many MET–estimation models are device-specific, require individual calibration, or are validated only under laboratory settings, which limits their generalization to everyday mobile contexts. In contrast, ENMO-based mappings are simple, interpretable, and sensor-agnostic, making them promising candidates for lightweight EE estimation on commodity wearables.

Prior work suggests that ENMO–MET relationships may vary by activity type, and that activity-specific EE models may improve estimation accuracy (Tabor et al., 2014). Because the goal of this paper is to develop a lightweight, generalizable EE estimator for mobile systems, we focus on relative MET patterns and physiological plausibility rather than precise calorimetric accuracy.

2.2 Human Activity Recognition and Prior Work on this Dataset

Human Activity Recognition (HAR) is often incorporated into EE estimation pipelines to identify which biomechanical or MET-based models should be applied for a given activity. In many commercial systems this requires explicit user input (e.g., selecting “start workout”), but automatic activity detection enables a more seamless user experience and supports continuous EE estimation. For the current study we rely on activity labels for evaluation and grouping (rather than for model selection), and we plan to use machine learning and potentially other low-power sensors to determine a user’s activity type and apply the appropriate MET formula.

Prior work has demonstrated accurate recognition of walking, jogging, stair ascent, and stair descent on the same dataset used in this study. In particular, the gait-cycle–averaged, shapelet-based HAR method introduced in (Ellison et al., 2023b) achieved efficient real-time classification on embedded devices. This confirms that the dataset contains clean, well-separated activity classes and provides the high-quality labels needed for indirect validation of MET-based EE estimation. While the activity labels identify the *type* of locomotion (e.g., walk vs. stairs), they do not fully determine intensity: even within a single activity class, intensity varies with speed, grade, cadence, and individual biomechanics. Our goal is therefore not to replace activity labeling, but to provide a lightweight, interpretable intensity estimate (in MET units) that can support within-activity comparisons and temporal summaries (e.g., identifying moderate-to-vigorous periods) without heart-rate sensing.

Future versions of our mobile system will integrate a HAR module to automatically select activity-specific EE mappings when warranted, as suggested by prior work on activity-dependent EE models (Tabor et al., 2014). This enables a modular pipeline in which HAR provides semantic structure to the accelerometer stream, while MET estimation provides lightweight intensity quantification without dependence on heart-rate or calorimetric instrumentation.

3 METHODS

This section describes the dataset, the EE estimation pipeline based on ENMO and MET mappings, feature extraction, and the indirect validation strategy used to evaluate EE estimates without calorimetric ground truth.

3.1 Dataset and Sensor Setup

Data were collected using ActiGraph GT9X triaxial accelerometers worn simultaneously on the wrist and hip. The devices recorded raw acceleration at a sampling frequency of 100 Hz. A total of 31 participants completed a structured activity protocol consisting of five activities: treadmill walking, outdoor/sidewalk walking, jogging, stair ascent, and stair descent. Treadmill walking was performed at 2.5 mph and treadmill jogging at 5.5 mph both at 0% grade. Outdoor/sidewalk walking was performed at a self-selected pace along a flat sidewalk. Each activity lasted approximately 2 minutes, yielding about 5.5 hours of labeled data.

The Actigraph GT9X Link activity monitor uses a research-grade 3-axis MEMS accelerometer with a dynamic range of approximately ±8 g and supports raw sampling rates from 30 – 100 Hz, housed in a compact 3.5 × 3.5 × 1 cm, 14 g enclosure suitable for long-duration ambulatory recording; the device also includes an inertial measurement unit (IMU) with gyroscope and magnetometer channels, although only the primary accelerometer was used in this study. In this study, devices were worn on the dominant wrist and the hip using manufacturer-provided straps to ensure consistent orientation and minimize slippage during activity.

Before data collection, both sensors were time-synchronized and secured to minimize motion artifacts. Each activity segment was trimmed to remove transition periods at the beginning and end, following best practices in wearable sensing research (Ellison et al., 2023a). Signals were then segmented into fixed-length windows of 5 seconds with 50% overlap, a common configuration for EE and activity-recognition pipelines (Issa et al., 2022). All subsequent feature extraction and MET estimation operate at the window level. Prior analyses on this dataset have shown that activity labels are clean and well-separated, supporting their use as ground truth for evaluating relative EE patterns.

3.2 Energy Mapping Pipeline

Gravitational acceleration was removed using the Euclidean Norm Minus One (ENMO):

$$ENMO = \sqrt{x^2 + y^2 + z^2} - 1.$$

Negative values were truncated to zero to correct for accelerometer noise. ENMO was computed sample-wise from raw triaxial acceleration and then averaged over each 5-second window prior to MET conversion. The epoch-averaged ENMO was then converted to metabolic equivalent (MET) values using published ENMO-based nonlinear mappings that are specific to sensor placement (Frey-law et al., 2024). In these models, ENMO is first mapped to oxygen consumption (VO_2 in ml·kg^{-1}·min^{-1}), which is subsequently converted to MET by normalization to the standard resting metabolic rate (3.5 ml·kg^{-1}·min^{-1}).

$$\mathrm{VO}_2^{hip} = 1.708 \cdot a^{0.442}, \tag{1}$$

$$\mathrm{MET}_{hip} = \max\left(1, \frac{\mathrm{VO}_2^{hip}}{3.5}\right), \tag{2}$$

$$\mathrm{MET}_{wrist} = \max\left(1, \frac{0.901 \cdot a^{0.534}}{3.5}\right). \tag{3}$$

Placement-specific equations were applied as reported in the original studies, and no mappings were transferred across sensor locations. A minimum of 1 MET was enforced to account for resting physiological processes. It is worth noting that although we compute kilocalories for interpretability during analysis, the mobile application context displays MET-based intensity levels only:

$$kcal = \frac{Time \times MET \times Weight \times 3.5}{200}.$$

3.3 Feature Extraction

For each 5-second window, we compute ENMO as the primary summary statistic because the MET estimation in this work relies on published ENMO-to-MET mappings (Sec. 3). In addition, we compute common time-domain features—mean, median, variance, and signal magnitude area (SMA)—over the windowed acceleration signal. These auxiliary features are not inputs to the ENMO-based MET equations reported in this paper; instead, they are retained for (i) exploratory analysis and data-quality checks (e.g., verifying expected increases in motion magnitude across activities), and (ii) supporting future versions of the pipeline that integrate automatic activity recognition (HAR) and potentially activity-dependent modeling.

We leave quantitative analysis of these auxiliary features for future work focused on activity recognition and model selection.

Because windowing was performed within pre-labeled activity segments, each window inherits the corresponding activity label, allowing us to group ENMO-derived MET estimates by activity type during validation.

3.4 EE Modeling and Indirect Validation

Because the dataset does not include calorimetric ground truth, we use the published ENMO-to-MET mappings as the primary EE model, rather than training a regression or deep-learning estimator. ENMO is computed per window, converted to MET via the appropriate formula, and aggregated into 30-second epochs.

For each subject and activity, we compute the mean MET per epoch. Kilocalorie equivalents are derived only for analysis and comparison but are not intended for end-user display.

Indirect validation replaces direct physiological validation and consists of three components:

1. **Consistency with Benchmark MET tables.** We compare activity-level mean MET estimates to benchmark values from the Compendium of Physical Activities (Ainsworth et al., 2011). For context, we report simple activity-level differences and percentage deviations and visualize the relationship using a scatter plot with a 1:1 reference line.
2. **Cross-Subject Stability.** We examine subject-level variability in predicted MET values for each activity using distributions and boxplots. Low between-subject variance indicates that estimates reflect activity intensity rather than idiosyncratic noise.
3. **Activity-Intensity Ordering.** We verify that predicted MET values preserve the expected ordering across locomotor tasks (e.g., jog > walk, and stair-related activities exceeding walking on average) using visual comparisons of activity-specific MET distributions.

We do not apply any post-hoc calibration or activity-specific correction factors; all MET estimates come directly from the published ENMO-based equations. Instead, we assess plausibility by comparing the resulting activity-level MET distributions to benchmark values reported in the Compendium of Physical Activities.

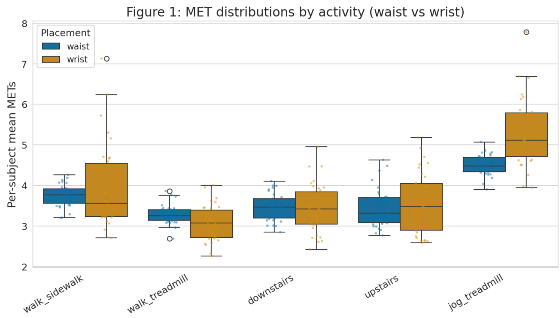

Figure 1: Cross-subject MET distributions by activity for waist and wrist placements. Each box shows the distribution of per-subject mean MET values for a given activity, with points representing individual subjects.

These analyses do not substitute for direct EE measurement, but they provide evidence that the ENMO-based model produces physiologically plausible intensity patterns consistent with established MET benchmarks.

4 RESULTS

4.1 Per-Activity MET Patterns

Aggregated results show the expected progression in activity intensity: walking activities fall in the light-to-moderate range, stair-related activities occupy a moderate-to-vigorous range, and jogging produces the highest MET values. Variation between participants is smaller than variation between activities, suggesting that the ENMO-based model captures essential differences in intensity rather than subject-specific noise. Quantitatively, activity-level MET estimates showed clear separation across locomotor tasks. Across subjects, jogging produced the highest mean MET values (median $\approx$ 4.8–5.0 METs), followed by stair-related activities (median $\approx$ 3.6–4.1 METs), with walking activities consistently lower (median $\approx$ 3.2–3.9 METs). Within-activity variability across subjects was substantially smaller than between-activity differences, and no subject exhibited an inversion in which walking exceeded jogging in mean MET. These results indicate that the ENMO-based model preserves expected relative intensity ordering at the subject level.

Table 1 summarizes the per-subject mean MET values for each activity, and Figure 1 visualizes these distributions. The boxplots show that subjects performing the same activity exhibit similar MET levels, while still reflecting natural individual variation.

These results show that walking activities cluster around 3.4–4.2 METs, stair-related activities around

Table 1: Benchmark MET values from the Compendium of Physical Activities compared with activity-level mean MET estimates derived from waist-mounted accelerometer data.

Activity	Mean MET	SD
Downstairs	4.81	0.33
Jogging	4.74	0.35
Upstairs	3.70	0.46
Walk (Mixed)	4.02	0.60
Walk (Sidewalk)	4.23	0.26
Walk (Treadmill)	3.47	0.29

Table 2: Benchmark vs. estimated MET values.

Activity	Bench.	Est.	% Err.
Downstairs	5.0	4.81	-3.8%
Jogging	8.0	4.74	-40.8%
Upstairs	6.0	3.70	-38.3%
Walk (Sidewalk)	3.5	4.23	+20.8%
Walk (Treadmill)	3.5	3.47	-0.9%

3.7–4.8 METs, and jogging near 4.7–5.5 METs, reflecting the expected ordering of activity intensities. The slightly higher value for stair descent relative to jogging reflects the known ENMO saturation effect during vigorous cyclic motion as well as strong impact peaks during descent, a behavior consistent with prior ENMO-based analyses.

4.2 Benchmark Comparison

We also compare activity-level mean MET estimates to benchmark values from the Compendium of Physical Activities (Ainsworth et al., 2011) in Table 2. Walking and stair descent estimates are close to their reference values and fall within expected variability. Jogging and stair ascent show larger deviations, which is reasonable given protocol differences, population differences, and the fact that ENMO-to-MET equations were derived on different datasets. This deviation is consistent with prior findings that ENMO-based wrist equations systematically underestimate vigorous activities such as jogging and running, in part because ENMO was calibrated primarily on light–to–moderate movement and is known to saturate at higher intensities (Hidalgo Migueles et al., 2017). Overall, the estimator reproduces both the expected ordering and approximate magnitude of activity-specific MET levels.

Figure 2 provides a compact visualization of agreement and deviation relative to benchmark MET values, complementing the distributional view shown in Figure 1.

The slightly higher MET estimate for stair de-

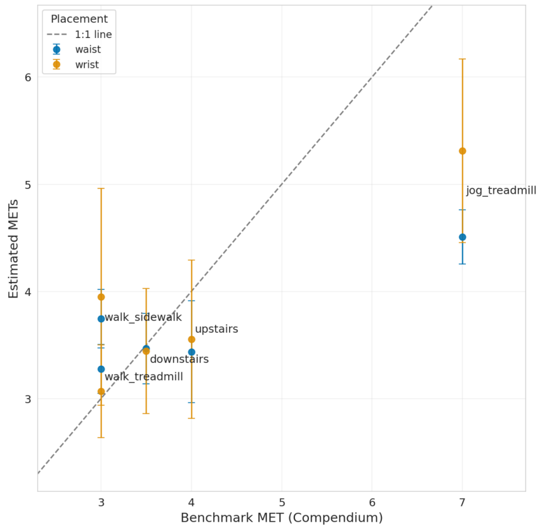

Figure 2: Estimated versus benchmark MET values by activity for waist and wrist placements, with a dashed 1:1 line indicating ideal agreement.

scent relative to jogging highlights a known limitation of ENMO-based mappings. ENMO has been shown to saturate at higher movement intensities (Bakrania et al., 2016) and to be sensitive to impact-related acceleration peaks, such as those occurring during stair descent. In addition, differences between the jogging protocol used in this study (e.g., treadmill speed and stride dynamics) and the populations and conditions under which the original ENMO-to-MET equations were derived likely contribute to this inversion relative to benchmark MET ordering. Accordingly, this method is not intended for precise vigorous-intensity EE estimation.

Waist-mounted sensors show more stable and interpretable MET patterns across locomotor tasks compared to wrist-mounted sensing, with reduced overlap between walking, stair-related activities, and jogging at the group level. This supports the suitability of waist-mounted accelerometers for lightweight EE estimation in mobile health applications where relative intensity and not caloric precision is the primary objective.

5 DISCUSSION

Our findings suggest that accelerometer-only models based on ENMO and published MET equations can produce meaningful indicators of energy expenditure that align with labeled activity intensity. Rather than attempting to estimate exact caloric output, this approach supports qualitative insight into movement patterns across light, moderate, and vigorous activity. For applications that intentionally avoid calorie-based feedback—including those informed by intuitive eating principles—such relative intensity information is sufficient and often preferable.

From a human-centered perspective, MET-based activity summaries can support psychologically safe feedback in mobile wellness systems. By contextualizing movement as part of daily bodily rhythms rather than as a compensatory metric, the system can help users interpret their activity without reinforcing calorie tracking or restrictive behaviors. For example, instead of reporting caloric expenditure, the system might indicate that the user had a period of moderate or vigorous movement that could contribute to hunger patterns or recovery needs.

Because this dataset does not include calorimetric ground truth, our validation relies on internal and external consistency checks rather than absolute physiological accuracy. Since MET values are derived via published ENMO-to-VO_2 mappings rather than directly measured oxygen consumption, the reported estimates should be interpreted as relative intensity indicators rather than absolute physiological ground truth. The agreement between predicted MET patterns and both activity labels and benchmark MET ranges suggests that the ENMO-based equations capture meaningful distinctions in intensity, even if fine-grained accuracy remains unverified. These results indicate that accelerometer-only MET estimation can be a practical component in mobile systems where relative intensity is more valuable than precise metabolic quantification.

Key limitations include the constrained nature of the activity protocol, the limited number of movement types, and the absence of physiological EE reference measurements. Future work will expand to more diverse activities and free-living environments, collect calorimetry or heart-rate–based EE ground truth for direct validation, and examine robustness across sensor brands, placements, and wearing styles. Additional research could also explore personalized calibration methods, which may reduce between-subject variability and further improve the ecological validity of accelerometer-only EE estimation.

We note that stair descent produced slightly higher mean MET than stair ascent in this dataset. This inversion relative to some MET tables may reflect the sensitivity of ENMO to impact peaks and braking forces during descent, as well as protocol-specific factors (cadence, step height, and handrail use) that influence wrist/hip acceleration patterns. This highlights that ENMO-based mappings can deviate from compendium values for specific locomotor subtypes and motivates future validation with physiological ground truth.

6 APPLICATION IN THE INTUITIVE EATING APP

The estimated MET-based intensity levels will be incorporated into a mobile intuitive eating system that also uses NLP and nutrition APIs to analyze logged meals. Rather than presenting calories, the app contextualizes movement as one component of overall bodily awareness. For example:

> "Today's activity pattern shows moderate movement, supporting your natural hunger rhythm."

In the full system, accelerometer data from a smartphone or wearable device are processed either on-device or in the cloud to produce daily or weekly summaries of movement intensity zones. These summaries are then presented alongside qualitative nutritional reflections generated by the NLP-based meal logging component, enabling users to consider how movement and nourishment interact over time without exposure to calorie counts.

MET-based insights can also support gentle, descriptive feedback such as "you had more vigorous movement than usual today" or "most of your activity this afternoon was light." This framing aligns with intuitive eating principles, emphasizing self-awareness and body attunement rather than prescriptive targets or compensatory exercise metrics.

7 CONCLUSIONS

This paper presented a lightweight method for estimating MET-based energy expenditure using only accelerometer data, with the goal of supporting calorie-free movement insights in mobile health applications. The proposed ENMO-based pipeline produced intensity patterns that aligned with labeled activity structure and benchmark MET ranges, despite the absence of calorimetric ground truth.

More broadly, the findings demonstrate that simple, accelerometer-only models can provide meaningful indicators of relative activity intensity suitable for real-time, privacy-preserving deployment on wearable or mobile platforms. When integrated into wellness tools, such MET-based summaries can support descriptive, non-prescriptive feedback that avoids calorie-centric framing.

Future work will expand data diversity, incorporate physiological ground truth for direct validation, and evaluate the approach in free-living environments. Additional research will also examine how MET-based insights influence user experience when combined with nutrition-related reflection tools in an intuitive-eating–oriented system.

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