Objective assessment of physical activity at home: a comparison of a novel floor-vibration monitoring system, wearable activity trackers, and indirect calorimetry measurements

Yuki Nakajima, Asami Kitayama, Yuji Ohta, Nobuhisa Motooka, Mayumi Kuno-Mizumura, Motohiko Miyachi, Shigeho Tanaka, Ishikawa-Takata Kazuko, Julien Tripette

Submitted to: JMIR Formative Research
on: August 16, 2023

Table of Contents

Objective assessment of physical activity at home: a comparison of a novel floor-vibration monitoring system, wearable activity trackers, and indirect calorimetry measurements

Yuki Nakajima[1*] BSc; Asami Kitayama[1*] MSc; Yuji Ohta[1] PhD; Nobuhisa Motooka[1] PhD; Mayumi Kuno-Mizumura[2] PhD; Motohiko Miyachi[3, 4] PhD; Shigeho Tanaka[3, 5] PhD; Ishikawa-Takata Kazuko[6, 7] PhD; Julien Tripette[8, 1, 3] PhD

[1]Department of Human-Environmental Sciences Ochanomizu University Bunkyo JP
[2]Department of Dance Ochanomizu University Bunkyo JP
[3]National Institute of Health and Nutrition National Institutes of Biomedical Innovation, Health and Nutrition Ibaraki JP
[4]Faculty of Sport Sciences Waseda University Tokorozawa JP
[5]Faculty of Nutrition Kagawa Nutrition University Sakado JP
[6]Faculty of Applied Biosciences Tokyo University of Agriculture Setagaya JP
[7]National Institute of Health and Nutrition , National Institutes of Biomedical Innovation, Health and Nutrition Ibaraki JP
[8]Center for Interdisciplinary AI and Data Science Ochanomizu University Bunkyo JP
[*]these authors contributed equally

Corresponding Author:
Julien Tripette PhD
Center for Interdisciplinary AI and Data Science
Ochanomizu University
2-1-1 Otsuka
Bunkyo
JP

Abstract

Background: This study tests an original floor-vibration monitoring system to quantify housework-related physical activity.

Objective: To assess the validity of step-count and physical activity intensity predictions of the novel floor-vibration monitoring system with respect to the actual number of steps and indirect calorimetry measurements. The accuracy of predictions was also compared with the ones of research-grade devices (ActiGraph GT9X).

Methods: The Ocha-House is an independent experimental house located in Tokyo, in which high-sensitivity accelerometers are installed on the floor to monitor vibrations. A data processing software was designed to process floor-vibration signals and compute the three following quantitative indexes: floor vibration quantity, step-count and moving distance. Eleven participants performed four different housework activities, wearing Actigraph GT9X monitors on both the waist and wrist for 6 min each. The floor-vibration data were collected and the energy expenditure was measured by using the Douglas bag method, to determine the actual intensity of activities.

Results: Significant correlations ($P<.001$) were found between the quantity of floor vibrations, the estimated step-count, the estimated moving distance, respectively, and the actual activity intensities. The step-count parameter extracted from the floor vibration signal was found to be the best predictors ($r2=0.82$, $P<.001$). Multiple regression models that include several floor vibration-extracted parameters showed a strong association with the actual activity intensities ($r2=0.87$). The step-count and intensity predictions made by the floor vibration monitoring system were more accurate that the ones of the ActiGraph monitors.

Conclusions: Floor vibration monitoring systems seem able to produce valid quantitative assessments of the physical activity for housework activities. In the future, connected smart home systems integrating this type of technology could be used to perform continuous and accurate evaluations of the daily physical activity.

(JMIR Preprints 16/08/2023:51874)
DOI: https://doi.org/10.2196/preprints.51874

Preprint Settings

1) Would you like to publish your submitted manuscript as preprint?
Please make my preprint PDF available to anyone at any time (recommended).
Please make my preprint PDF available only to logged-in users; I understand that my title and abstract will remain visible to all users.
Only make the preprint title and abstract visible.
✓ **No, I do not wish to publish my submitted manuscript as a preprint.**
2) If accepted for publication in a JMIR journal, would you like the PDF to be visible to the public?
✓ **Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).**
Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain v
Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in <a href="http

Original Manuscript

Original Paper

Yuki Nakajima[1]; Asami Kitayama[1], MSc; Yuji Ohta[1], PhD; Nobuhisa Motooka[1], PhD; Mayumi Kuno-Mizumura[2], PhD; Motohiko Miyachi[3,4], PhD; Shigeho Tanaka[4,5], PhD; Kazuko Ishikawa-Takata[4,6], PhD; Julien Tripette[1,4,7], PhD.

[1] Department of Human-Environmental Sciences, Ochanomizu University, Bunkyo, Tokyo, Japan
[2] Department of Dance, Ochanomizu University, Bunkyo, Tokyo, Japan
[3] Faculty of Sport Sciences, Waseda University, Tokorozawa, Saitama, Japan
[4] National Institute of Health and Nutrition, National Institutes of Biomedical Innovation, Health and Nutrition, Ibaraki, Osaka, Japan
[5] Faculty of Nutrition, Kagawa Nutrition University, Sakado, Saitama, Japan
[6] Faculty of Applied Biosciences, Tokyo University of Agriculture, Setagaya, Tokyo, Japan.
[7] Center for Interdisciplinary AI and data science, Ochanomizu University, Bunkyo, Tokyo, Japan

Corresponding Author:
Julien Tripette, PhD
Center for Interdisciplinary AI and data science,
Ochanomizu University,
2-1-1 Otsuka, Bunkyo,
Tokyo, 112-8610,
Japan
Phone: 81 359785105
Email: tripette.julien@ocha.ac.jp

Objective assessment of physical activity at home: a comparison of a novel floor-vibration monitoring system, wearable activity trackers, and indirect calorimetry measurements

Abstract

Background: Self-monitoring of physical activity is an effective strategy to promote active lifestyles. However, accurately assessing physical activity remains challenging in certain situations. This study evaluates a novel floor-vibration monitoring system to quantify housework-related physical activity.

Objective: To assess the validity of step-count and physical behavior intensity predictions of the novel floor-vibration monitoring system in comparison to the actual number of steps and indirect calorimetry measurements. The accuracy of predictions is also compared with the ones of research-grade devices (ActiGraph GT9X).

Methods: The *Ocha-House*, located in Tokyo, serves as an independent experimental facility equipped with high-sensitivity accelerometers installed on the floor to monitor vibrations. A dedicated data processing software was developed to analyze floor-vibration signals and calculate three quantitative indexes: floor vibration quantity, step-count and moving distance. Ten participants performed four different housework-related activities, wearing Actigraph GT9X monitors on both the waist and wrist for 6 min each. Concurrently, floor-vibration data were collected, and the energy expenditure was measured by using the Douglas bag method to determine the actual intensity of activities.

Results: Significant correlations (P<.001) were found between the quantity of floor vibrations, the estimated step-count, the estimated moving distance, respectively, and the actual activity intensities. The step-count parameter extracted from the floor vibration signal emerged as the most robust predictor (r^2=0.82, P<.001). Multiple regression models incorporating several floor vibration-extracted parameters showed a strong association with the actual activity intensities (r^2=0.88, P<.001). Both step-count and intensity predictions made by the floor vibration monitoring system exhibited greater accuracy than those of the ActiGraph monitors.

Conclusions: Floor vibration monitoring systems seem able to produce valid quantitative assessments of the physical activity for some selected housework-related activities. In the future, connected smart home systems integrating this type of technology could be used to perform continuous and accurate evaluations of the physical behaviors throughout the day.

Keywords: Smart-home system; physical behavior; physical activity; activity tracker; floor vibration; housework-related activity; home-based activity.

Introduction

Pieces of evidences associate regular physical activity with lower risks for mortality and noncommunicable diseases [1], encouraging researchers, policy makers and health care companies to develop strategies for the promotion of active lifestyles. The self-monitoring of physical behavior is one approach that has been described as effective for helping people increase their level of physical activity [2-5]. The recent expansion of the activity tracker device market has certainly opened new perspectives for the promotion of active behaviors [3, 6].

Technology that enables the objective assessment of physical behaviors has evolved considerably over the past decades [7]. Modern activity trackers are generally worn at the waist or the wrist and while the most recent devices usually feature multiple sensing abilities, the evaluation of physical behaviors mostly results from the treatment of acceleration data acquired by an integrated three-axis microelectromechanical accelerometer sensor chip [8]. Software tools are able to compute a wide range of parameters related to physical behaviors such as sedentary time, step-count and estimated energy expenditure (EE). [9]. Activity tracker devices can be paired with smartphone applications, transforming smartphone handsets into genuine hubs for the monitoring of physical activity and sedentary behaviors. While waist- and wrist-worn activity tracker devices have been linked to inaccurate EE predictions [10-12], the emergence of the 5G/IoT devices opens up the room for more accurate and continuous monitoring where multiple connected devices can collect a wealth of information about people physical behaviors throughout the day. In such a connected environment, and while housework-related activities account for a significant proportion of daily physical activity in some populations [13], smart home systems could provide crucial information to 1) support the continuity of the monitoring of physical activity and sedentary behaviors when people are staying at home by allowing them to remove their wearable activity tracker device, and 2) improve the accuracy of EE predictions related to home-based activities. However, while various smart home projects have already included technological features allowing monitoring the physical behaviors of the occupants, to date, the information has mainly been used as input to smart appliances for adapting the living environment, assisting occupants with disabilities or optimizing domestic energy consumption [14-17]. In these projects, various monitoring technology devices have been considered: motion sensors, low-resolution video cameras, Kinect systems (Microsoft, Washington), and accelerometer-based wearable monitors [16, 18-20]. Floors with sensing capabilities have also been developed. For instance, binary pressure detection floor systems have been utilized to detect the position of occupants [21,22]. Floor geophones and accelerometer sensors have been used to locate footsteps or evaluate room occupancy [23,24]. Unfortunately, none of these projects have prioritize the objective and quantitative assessment of physical behaviors with the ultimate goal of providing lifestyle-oriented feedback to the occupants. Nevertheless, smart-home systems capable of monitoring physical activity and sedentary behaviors, while providing feedback to the occupants, hold the potential to encourage individuals to adopt more active and healthier behaviors throughout the day [2-5].

In this study, the floor vibration measurement system of the experimental *Ocha-House* is used to collect information about the floor vibrations generated by the occupant and estimate EE and step-count. A structured experiment consisting of the completion of 4 typical home-based activities was conducted to assess the validity of these estimations with respect to the actual measurements performed by indirect calorimetry (EE) and direct observation (step-count). The estimations of the floor vibration monitoring system are also compared to the ones of waist- and wrist-worn research-grade activity tracker devices. It is hypothesized that the floor vibration monitoring system is capable of correct predictions of EE.

Methods

The *Ocha-House* project

The experimental *Ocha-House* is in Bunkyo district in the central area of the Tokyo metropolitan region. The project was originally designed as a ubiquitous computing house allowing the mounting of various sensing devices [25]. According to Japanese standards, the *Ocha-House* corresponds to an extended 1LDK dwelling, i.e., a one-bedroom apartment with a kitchen separated from the living and dining areas. An overview of the building and experimental area is depicted in Figure 1.

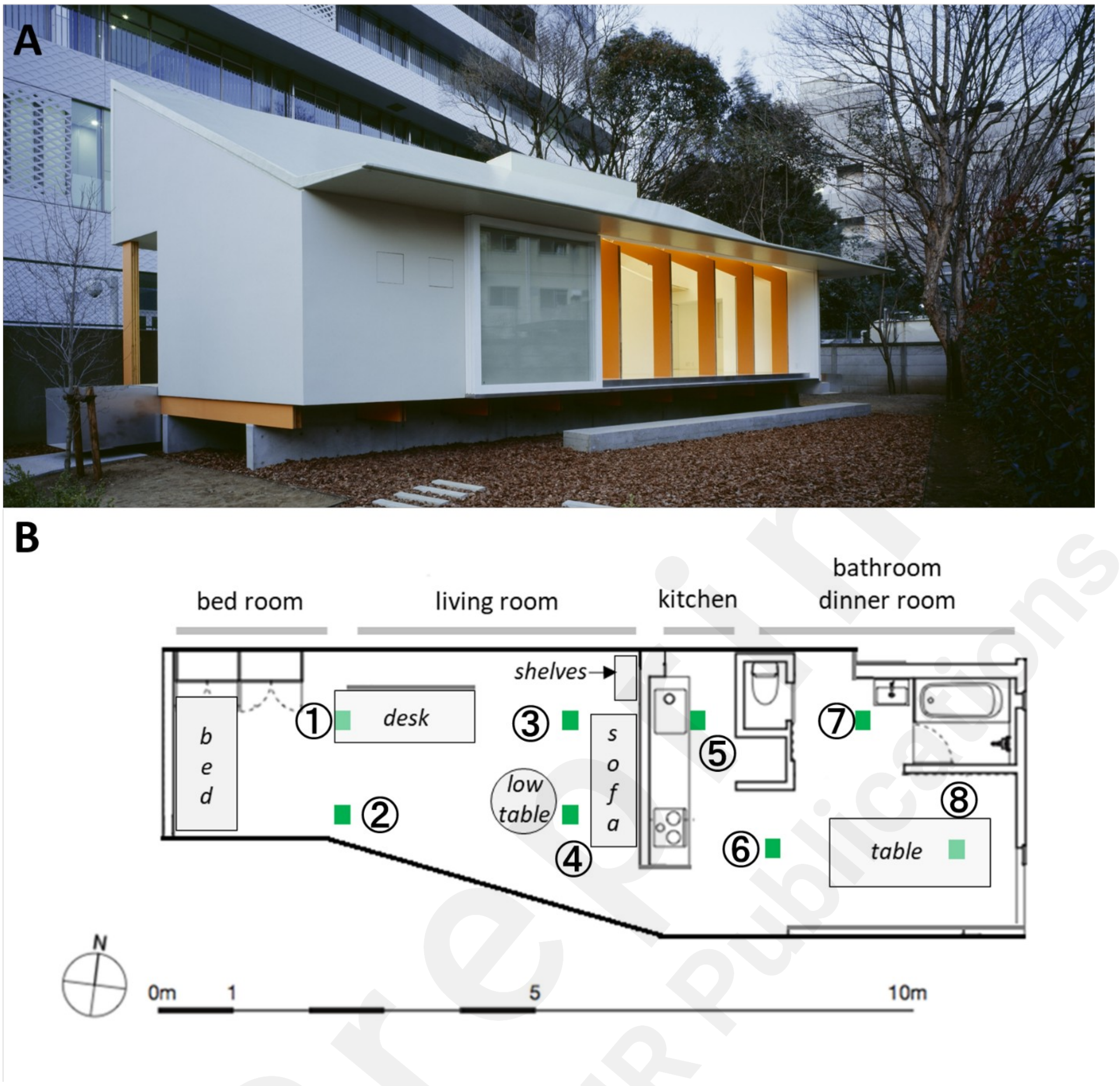

Figure 1. Overview of the *Ocha-House* and the experimental area. (A) External view of the building (image captured from southwest corner of the yard); (B) view from above the experimental area with pieces of furniture indicated in light gray, and green squares (labeled: ①, ②, ③, ④, ⑤, ⑥, ⑦, ⑧) indicating sensor positions. The house comprises two distinct areas separated by a wall. The west-side features a fully open space housing a bedroom corner and a living room without any additional partition wall. On the east-side, the kitchen and dining room are interconnected through an open space. The toilet and bathroom corners are situated in enclosed spaces on the east-side of the building.

The total surface of the experimental area was 42 m2 (Figure 1B). Eight high-sensitivity uniaxial accelerometers (Shear-type/vibration pickup PV-87, Rion Co., Ltd., Japan) were installed on the floor to measure the floor vibrations occurring on the experimental surface. The PV-87 sensor characteristics are specified as follows by the manufacturer: charge sensitivity: ±40 pC/(ms-2), range of detection: 1–3000 Hz, dimensions: 24(Hex) x 30.5(H) mm, mass: 115 g. The optimal number of sensor units and their locations were determined through a series of preliminary experiments. These experiments consisted in progressively increasing the sensitivity setting of the sensors and the number of units placed on both the West and East sides of the Ocha-House. The operation continued until the coverage was deemed sufficient to detect human motion across all parts of the experimental surface. Data related to these preliminary experiments are not presented. The sensors were mounted on the floor using dual-side tape as recommended by the manufacturer and connected to four UV-16 2-channel charge amplifiers (Rion Co., Ltd., Japan) configured in accordance with the manufacturer recommendations. The floor vibration data acquisition was performed using USB-6008 data acquisition devices (National Instrument Corp., Texas), and a laptop equipped with MATLAB 2015b and the necessary data acquisition toolbox (MathWorks Inc., Massachusetts). The signal was digitized at a 100-Hz sampling rate with a resolution of 12 bits. The above-described system is described thereafter as the “floor vibration monitoring system”.

Study protocol

Ten women participants engaged in four activities in the *Ocha-House*. Participants were recruited on the campus of the Ochanomizu University campus, which is a women university. They were selected based on the inclusion criterion of being over 18 years old, with the exclusion criterion being physical imbalance. Participant characteristics are summarized in Table 1, and details of the four activities performed at the *Ocha-House* are presented in Figure 2. Prior to the commencement of the experiment, each participant completed a brief walking trial in the *Ocha-House*, lasting approximately 1 minute. Two researchers with expertise in gait analysis visually determined the gait type of each participant, specifically identifying whether they exhibited a heel strike, or lighter mid- or fore-foot strike landing. The walking trial revealed that all participants could be categorized into either the heel-strike landing, or mid- or fore-foot strike landing categories, with no other gait types observed. All experiments were conducted without any footwear, including sleepers. Nine participants wore socks. One participant was not wearing sock the day of the experiment and completed the protocol barefoot.

Table 1. Participant characteristics.

Number of participants	Age (years)	Body weight (kg)	BMI (kg / m^2)[a]	Gait type (Heel strike / mid- or fore-foot strike)[b]
10	24±7	47±6	19±1	3/7

[a]BMI: body mass index.

[b]The column “gait type” refers to the number of participants presenting a strong heel strike during the walking gait cycle as opposed to participants who presented a lighter mid- or fore-foot strike landing. The gait type of the participants was determined visually during the walking calibration trial.

Figure 2. Images of the experiment. (A) Sitting and watching videos; (B) Ironing, folding, and hanging clothes; (C) Cooking, setting the table, and serving food; (D) Cleaning the room.

The four activities were selected from the “inactivity quiet/light” or “home activities” categories of the compendium of physical activities [26,27]. The metabolic equivalent of task (MET) values, indicating the intensity of each activity, are reported in the compendium as follows:

- Sitting and watching videos, hereafter referred as *sitting* (approximately 1.3 MET, activity code: 07020).
- Ironing, folding, and hanging clothes, hereafter referred as *ironing* (1.8–2.0 METs, activity codes: 05070 and 05090).
- Cooking, setting the table, and serving food, hereafter referred as *cooking* (approximately 2.5 METs, activity codes: 05051 and 05052).
- Cleaning the room, hereafter referred as *cleaning* (approximately 3.3 METs, activity code: 05030).

Each activity lasted 6 min. To balance the contribution of the three tasks within “cooking, setting the table, and serving food,” and considering the volume of the Douglas bag used for EE measurement (see section “Indirect calorimetry”), participants were orally given time information. This ensured that they spent approximately 40 seconds in each task every 2 minutes. The floor vibration monitoring system recorded floor vibrations, estimate the number of steps, and compute quantitative parameters as described in “Floor vibration signal treatment and data feature extraction”. The participants wore two ActiGraph GT9X monitors (ActiGraph LLC., Florida) at the waist and wrist, respectively. The 10-s epoch activity-count as well as the step-count prediction were recorded for each activity. Finally, Douglas bags were used during the last 2 minutes of each activity to collect the air expired by the participants, perform indirect calorimetry measurements, and obtained the actual EE. Throughout the experiments, the researchers stood quietly on an insulated part of the floor outside the experimental area to avoid producing any confounding vibrations. The experiments were video-recorded (data not shown). The experimental protocol was approved by the Ochanomizu university research ethics committee (#2018-18). All participants gave their written informed consent.

Floor vibration signal treatment and data feature extraction

The 8-sensor floor vibration data of each 6-min activity corresponded to eight time-series of 36000 samples. Raw data are expressed in Volt. For each series, the floor vibration signal was rectified and smoothed using a Butterworth filter. The vector norm of the 8 sensors was computed. A location-based calibration coefficient was applied to the vector norm at each data sample in order to uniformize vibration magnitudes throughout the experimental surface (Supplementary Material 1). The 3 following data features were extracted:

- *Floor-count*: For each participant and each activity, the 36000 sample values (6-min x 100Hz sampling rate) of the uniformized vector norm time series were summed to obtain the *floor-count* parameter.
- *Step-count*: data from the uniformized vector norm time series were cut in windows of 1 second with an overlap of 50%. For each window, the number of steps was computed using a standard peak detection algorithm configured to detect vibration peaks with a minimum prominence of 1.05 standard deviation and a minimum interval of 250 milliseconds [28]. The *step-count* parameter was computed for each activity of each participant by summing the number of unique peaks throughout the activity (6min). The step-count parameter is used as both a data feature allowing the prediction of EE and a physical activity parameter to be compared with the direct observations and the outcomes of the waist- and wrist-worn ActiGraph devices.
- *Moving-distance*: the uniformized vector norm time series were cut into windows of one second and averaged for each window. The window average was compared to a criterion value calculated for each individual from data collected during the walking trial, to determine whether the participant was moving. Then, the filtered data of the 8-sensor time series corresponding to the windows where the participant was moving were used to compute her location in the house. The distances between all locations taken sequentially were summed throughout each activity to obtain the *moving-distance* parameter (6min). This parameter has been tested and validated against the moving distance estimated from the observation of video records (Supplementary Material 2, Figure S2-1).

The signal treatment and computation of the 3 above-described parameters was performed using tool boxes included in the SciPy library [29]. An overview of the whole data processing is given in Figure 3.

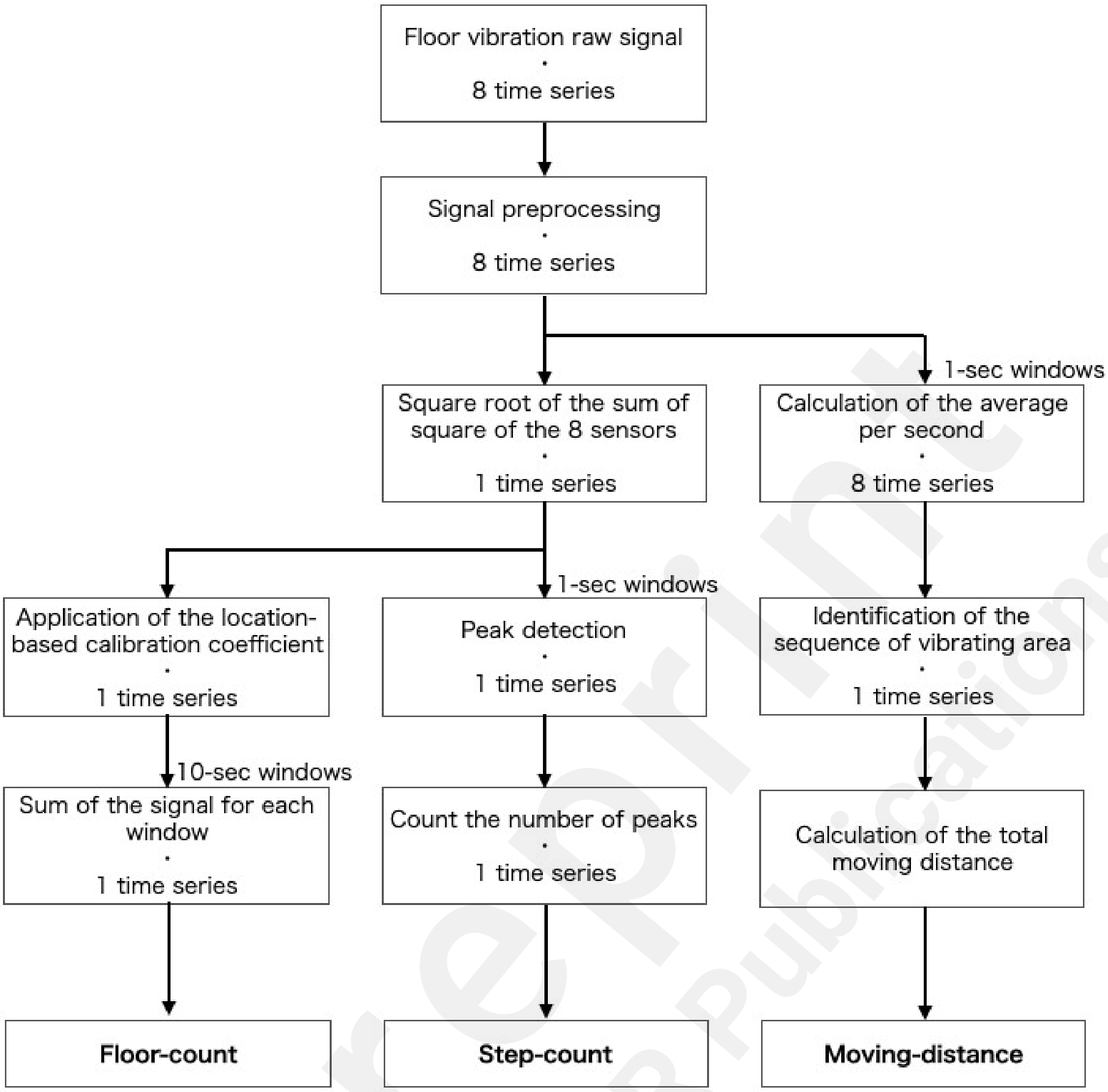

Figure 3. Floor vibration signal flow processing chart. From 8 time series of raw signals to the extraction of 3 floor vibration-based data features.

Actigraphy

Participants were equipped with two ActiGraph GT9X monitors worn at the waist and wrist, respectively. The waist-worn device was positioned near the right hip of the participant, on the belt or on the upper edge of the skirt or trouser bottom. An elastic belt provided by the manufacturer was used when the clothes worn by the participant did not allow mounting tightly the monitor. The wrist-worn GT9X device was mounted tightly on the nondominant hand, always in the same direction. The two monitors were mounted by the same experimenter for all participants. The ActiGraph monitor data were collected in 1-s epochs. The 10-s epoch *activity-count* data were extracted from the wrist- as well as waist-worn devices and the "Crouter adult (2010)" equation was used to compute EE predictions (ActiLife 6, ActiGraph LLC., Florida) [30]. This algorithm uses a refined two-regression model to discriminate between walking and lifestyle activities. In the present study, the activity intensities are expressed in MET (i.e., EE / participant weight / 6 min). The number of steps estimated by the waist- and wrist-worn monitors were also recorded.

Indirect calorimetry

The actual EE was measured using the Douglas bag method during the last 2 minutes of each activity. The air composition of the bags was analyzed using a mass spectrometry gas analyzer (ARCO-1000; Arco System, Kashiwa, Japan) calibrated on each experimental day in accordance with the manufacturer instruction. The gas volume was determined using a gas meter (DC-5; Shinagawa, Tokyo, Japan). The EE was estimated from the oxygen consumption (VO2) and carbon dioxide production (VCO2) using the Weir formula (i.e., 3.9 VO2 + 1.1 VCO2). In addition, the resting metabolism rate of each participant was evaluated prior to the experiment. The participant lied for 15 minutes on the bed of the *Ocha-House* and the expired air was collected during the last 2 minutes. Then, the actual MET value of each activity was calculated as the activity EE divided by the resting metabolic rate.

Video recording

The experimental sessions were video recorded using an Arrows M03 smartphone (Fujitsu Ltd., Tokyo, Japan) or an iPad Mini 3 (Apple, California). Two independent investigators inspected the videos and counted the number of actual steps for the four activities of each participant. In the present study, a “step” is defined as the shift of the body weight support from one leg to the other, which includes a single-leg support phase and occurs at least partially on the anterior-posterior axis.

Statistical analysis

The four activities were compared for the *floor-count*, *step-count*, *moving-distance* parameters using an ANOVA or the Kruskal-Wallis test and multiple comparison procedures (Tukey or Nemenyi tests) were performed to locate differences. The same analysis was conducted for parameters extracted from waist- and wrist-worn GT9X monitors and for the indirect calorimetry measurements. The relationships between the actual intensities measured by indirect calorimetry and *floor-count*, *step-count*, *moving-distance*, respectively, were investigated using single linear regression tests. Multiple regression models were used to explore the relationship between different combinations of descriptors, including *floor-count*, *step-count*, and *moving-distance*, and the actual intensities measured by indirect calorimetry. The analysis was conducted in a hierarchical fashion. First, the regressions were only performed on floor vibration extracted parameters. Second, the participant characteristics (i.e., body weight, gait type) were included among the model descriptors. Additional hierarchical models are presented in Supplementary Material 2. The model with the highest R^2 value best explained the variation in the data and was selected for subsequent testing. Finally, mixed model ANOVA and post-hoc pairwise operations were used to compare the performance of the best models built upon data obtained with the floor vibration-based monitoring system, the waist- and the wrist-worn GT9X monitors, against the actual intensity and the actual number of steps.
The underlying assumptions of each test were evaluated prior to conducting the analysis. Data are presented in text as mean ± standard deviation. The statistical analysis was performed using the following Python libraries: StatsModels (0.13.2), Pingouin (0.5.3), and Scikit-Posthocs (0.7.0) [31,32].

Results

Actual intensities and number of steps

Activity intensities calculated from indirect calorimetry measurements were as follows: 1.2±0.2 MET for the sitting behavior, 1.9±0.4 for the ironing activity, 2.5±0.4 for the cooking activity, and

3.7±0.6 for the cleaning activity (Figure 4A). Pairwise comparisons indicate significant differences in intensity between *sitting* and *cooking*, between *sitting* and *cleaning* and between *ironing* and *cleaning* (P<.05). The actual number of steps were as follows: 0±0 for *sitting*, 48±36 for *ironing*, 133±35 for *cooking*, and 281±48 for *cleaning* (Figure 4B). Pairwise comparisons indicate significant differences in steps between *sitting* and *cooking*, between *sitting* and *cleaning*, *ironing* and *cleaning* (P<.05).

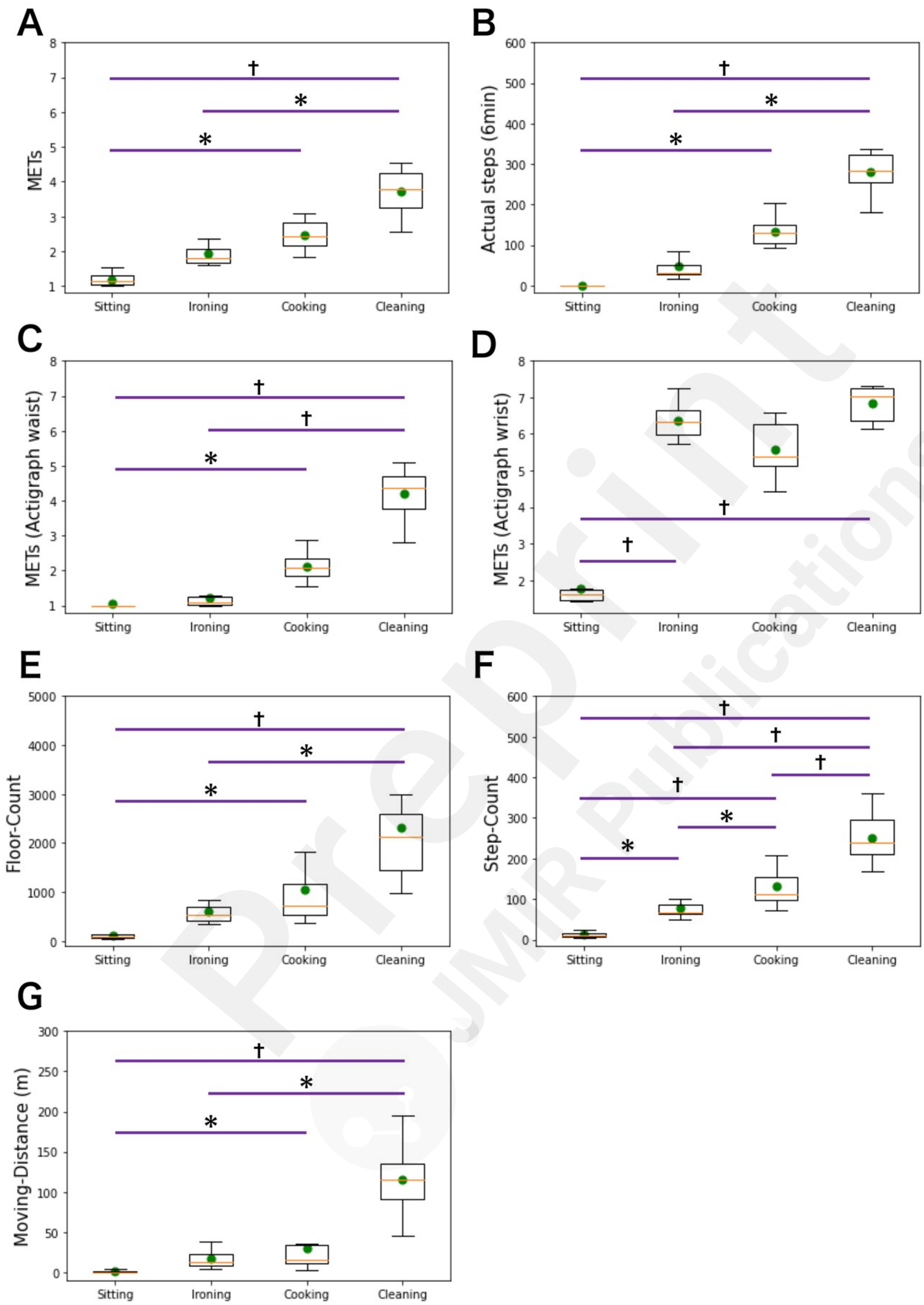

Figure 4. Comparison between the four experimental home activities. (A) Actual intensities (indirect calorimetry evaluation); (B) Actual number of steps (video observation); (C) Activity intensity predicted by the waist-worn ActiGraph GT9X device; (D) Activity intensity predicted by the wrist-worn ActiGraph GT9X device; (E) floor vibration-based computed *floor-count*; (F) floor vibration-based computed *step-count*; (G) floor vibration-

based computed *moving-distance*. The intensity predictions of the GT9X monitors were computed using the "Crouter adult (2010)" equation [30]. Yellow line: median. Green point: average. Outliers are not depicted. *: $P<.05$, †: $P<.001$.

Floor-count, step-count and moving-distance parameters computed from floor vibrations

The *floor-count* parameter (arbitrary unit) was as follows for each activity: 113±58 for *sitting*, 610±277 for *ironing*, 1046±748 for *cooking*, and 2323±1255 for *cleaning* the room (Figure 4E). Pairwise comparisons indicate significant differences in intensity between *sitting* and *cooking*, between *sitting* and *cleaning* and between *ironing* and *cleaning* respectively ($P<.05$). The estimated number of steps was as follows: 12±7.3 for *sitting*, 78±27 for *ironing*, 133±53 for *cooking*, and 251±59 for *cleaning* (Figure 4F) and pairwise comparisons indicated that the respective intensities of the four activities were all significantly different ($P<.05$). Finally, the *moving-distance* parameter scored as follows: 1.3±1.8 meter for *sitting*, 17±11 for *ironing*, 30±29 for *cooking*, and 115±39 for *cleaning* (Figure 4G). Pairwise comparisons indicate significant differences in intensity between *sitting* and *cooking*, between *sitting* and *cleaning* and between *ironing* and *cleaning*, respectively ($P<.05$). Furthermore, a significant correlation was found between the *moving-distance* outcomes computed from the floor vibration signal and moving distances estimated from the video records (Supplementary Material 2, Figure S2-1).

Actigraphy

The waist-worn activity tracker estimated the activity intensities as follows: 1.1±0.2 MET for *sitting*, 1.2±0.3 for *ironing*, 2.1±0.4 for *cooking*, and 4.2±0.7 for *cleaning* (Figure 4C). The pairwise comparison analyses indicate significant differences between *sitting* and *cooking*, between *sitting* and *cleaning* and between *ironing* and *cleaning* respectively ($P<.05$). The estimated number of steps were as follows: 0.9±2.4 for *sitting*, 8.0±12 for *ironing*, 55±27 for *cooking*, and 165±51 for *cleaning* (Supplementary Material 2). The pairwise comparison analyses indicate significant differences between *sitting* and *cooking*, between *sitting* and *cleaning* and between *ironing* and *cleaning* respectively ($p<0.05$).

The wrist-worn activity tracker estimated the activity intensities as follows: 1.8±0.4 MET for *sitting*, 6.4±0.5 for *ironing*, 5.6±0.7 for *cooking*, and 6.8±0.4 for *cleaning* (Figure 4D). Pairwise comparisons indicate significant differences between *sitting* and *ironing* and between *sitting* and *cleaning* respectively ($P<.05$). The estimated number of steps were as follows: 11±5.7 for *sitting*, 177±39 for *ironing*, 131±37 for *cooking*, and 197±35 for *cleaning* (Supplementary Material 2). The pairwise comparison analyses indicate significant differences between *sitting* and *cooking* and between *sitting* and *cleaning* respectively ($P<.05$).

Results for the activity-count parameters of the waist- and wrist-worn devices are shown in Supplementary Material 2.

Relationship between the floor vibration-based outcomes and the actual activity intensities

As shown in Table 2, *floor-count*, *step-count* and *moving-distance* were significantly associated with the intensity of physical behaviors (r^2=0.56, r^2=0.82, r^2=0.66, $P<.001$). Combining the three parameters together allows raising the r^2 value to 0.84. Combining *floor-count*, *step-count*, *moving-distance* with participant personal characteristics, such as bodyweight and gait type, allows predicting the intensity of physical behaviors with an accuracy of 88% (Table 2). The results of additional hierarchical models are shown in Supplementary Material 2.

Table 2. Relationship between floor vibration-based parameters and actual activity intensities evaluated by indirect calorimetry.[a]

Models	Predictor variables	SPRC	*P*-value	r^2
Single regressions				
1	*floor-count*	0.745	< 0.001	0.56
2	*step-count*	0.904	< 0.001	0.82
3	*moving-distance*	0.815	< 0.001	0.66
Multiple regressions				
4	*step-count* *floor-count* *moving-distance*	0.971 -0.430 0.361	< 0.001 0.01 0.02	0.85
5	*step-count* *moving-distance* *floor-count* body weight gait type	0.916 0.259 -0.224 -0.080 -0.155	< 0.001 0.09 0.20 0.21 0.03	0.88

[a]Regression models combining two vibration parameters with or without participant characteristic parameters are shown in Supplementary Material 2. “Gait type” is a binary data (mid- or fore-foot strike vs. heel strike foot landing). SPRC: Standardized Partial Regression Coefficient.

Step-count and activity intensity predictions

The Mixed Anova Model showed a significant effect of the measurement method and significant interaction with the activity for both the predictions of the numbers of steps and activity intensities (*P*<.001).

Significant underestimations of the number of steps were noted for the waist-worn ActiGraph device predictions when all activities were considered together (Figure 5A, “total”). The wrist-worn device and the floor vibration system did not show any difference with the actual number of steps. When activities are considered separately, pairwise comparisons indicate that the wrist-worn Actigraph device underestimated the number of steps completed during *cleaning* but overestimated it for the *sitting* and *ironing* activities. The floor vibration-based predictions overestimated the number of steps for *sitting*.

Regarding the prediction of activity intensities, the pairwise comparison analyses revealed statistically significant overestimations for the wrist-worn ActiGraph device across all activities. The floor vibration system did not show any difference with the actual intensities evaluated by indirect calorimetry. Finally, the waist-worn ActiGraph device showed a slight but significant underestimation for the estimations of the *ironing* activity intensities. Results are shown in Figure 5.

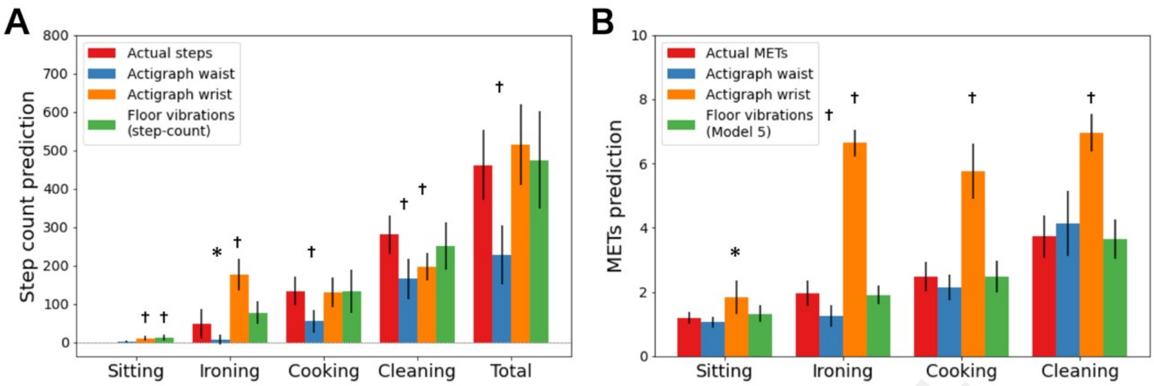

Figure 5. Comparison of prediction methods for each activity. (A) number of steps. (B) activity intensity. Energy expenditure measurements have been collected for 2 minutes over the 6 minutes of each activity. Therefore, comparisons of measurement methods for the total energy expenditure are not presented in this figure. In panel B, the green bar shows the prediction of the model with the highest coefficient of determination (see Table 2, model 5). MET: metabolic equivalent of task. The marks indicate a significant difference against the actual number of steps.*: *P*<.05, †: *P*<.001.

Discussion

Principal results

This study presented a novel quantitative method that uses the monitoring of floor vibrations for the evaluation of physical behaviors at home. The *floor-count*, *step-count* and *moving-distance* parameters were computed from the floor vibration signal. Statistical models combining these 3 parameters showed significant correlations with the actual energy expenditure measured in ten participants in a structured experiment that included four common home-based activities. In addition, the *step-count* parameter did not show any significant difference with the number of steps actually completed by the participant during the experiment. The predictions of the floor vibration monitoring system for both the activity intensity and number of steps were equal or more accurate than the ones performed by the Actigraphy method using the refined 2 regression model.

Floor vibration for the quantification of physical behaviors

The actual activity intensities measured by the indirect calorimetry for the four activities increased in accordance with the intensities presented in the compendium of physical activities [27], i.e., 1.2 vs. 1.3, 1.9 vs. 1.8–2.0, 2.5 vs. 2.5, and 3.7 vs. 3.3 MET for *sitting* (and watching video), *ironing* (and folding clothes), *cooking* (and setting the table), and *cleaning* the room, respectively (Figure 4A). The *floor-count*, *step-count* and *moving-distance* parameters also increased gradually for the four activities pointing to the feasibility of evaluating the intensity of physical behaviors in the home environment using the information provided by the floor vibrations (Figure 4E, 4F and 4G). Among them, *step-count* is the only parameter that showed significant differences between all four activities. The single regression analyses also pointed to a strong association between the *step-count* and the actual activity intensities (r^2 = 0.82, *P*<.001), while *floor-count* and *moving-distance* showed a weaker, but still significant, association with the actual activity intensities (r^2 = 0.56 and 0.66, respectively, *P*<.001 for both). These pieces of information taken together may suggest that the estimated number of steps extracted from the floor vibration signal could be used to make a reliable quantitative estimation of physical behaviors in home settings. All the three parameters have been designed to inform on the inhabitant motion. While, the *step-count* and *floor-count* parameters are able to capture the physical dimension of the movement, the *moving-distance* parameter adds a spatial dimension to the evaluation. The better performance of *step-count* alone compared to *moving-distance* alone, may be due to the location approximation inherent to the limited number of sensors that are used to cover the whole house surface (Supplementary Material 2). A step is detected and is not impacted by any approximation. On the other hand, *floor-count* may also be susceptible to inaccuracies, potentially due to variations in floor vibration wave attenuation. Factors influencing this attenuation include the proximity of furniture, their weight and contact surface with the floor, proximity of support beams and walls, as well as the irregular geometry of the *Ocha-House* floor area.

Despite the possible weaknesses of the *floor-count* and *moving-distance* parameters, multiple linear regression models combining *step-count, floor-count* and *moving-distance* still exhibited stronger associations ($r^2 \geq 0.85$, Table 2, and Supplementary material 2, Table S2-1). As showed in Table 2, the inclusion of the body weight and gait type parameters as descriptors greatly lowered the contribution of *floor-count* to the model. Indeed, despite *floor-count* does not correlate with either body weight and gait type (Supplementary Material 2, Table S2-2), it is still the only parameter extracted from floor vibrations able to capture quantitatively forces applied on the floor. Given that the actual body weight could be easily input into any smart-home system, the question of the relevance of extracting and using the *floor-count* parameter to make accurate predictions of energy expenditure remains open. Additional studies including a population with more heterogenous anthropometric characteristics may be needed to further address the question.

Finally, the ANOVA revealed that the predictions made by the floor vibration monitoring system also showed less deviations than the ones of the two research-grade ActiGraph GT9X monitors, for both the number of steps and activity intensity endpoints (Figure 5). The underestimations of the number of steps noted for the waist-worn Actigraph device may be related to walking gait characteristics when movements are performed in closed and narrow spaces. Such environments may not allow enough acceleration to meet the necessary signal processing threshold criteria required to count a step, as suggested elsewhere [33]. On the contrary, the overestimated number of steps observed for the wrist-worn device may be the result of confounding upper limb movements performed in a frequency range similar to the one of walking gait, which may occur in the course of completing housework-related activities.

Regardless of the performance of the Actigraph GT9X monitors and while no external validation experiment has been conducted, taken together, all these observations emphasize the good performance of the floor monitoring system for the quantitative evaluation physical behaviors performed in home settings.

Perspectives

While the market for wearable activity trackers is still in its growing phase [6], waist- and wrist-worn physical activity monitors have been associated with inaccurate predictions of daily physical activity, be they research- or consumer-grade devices [10-12]. During the past decade, the computation of accurate predictions for housework-related activities by traditional accelerometer-based activity tracker devices has been the object of specific software development [34,35]. However, the present study still showed statistical differences between the predictions made by the ActiGraph GT9X monitors and the actual values for both the number of steps and activity intensities. These observations emphasize the necessity of developing new methods able to evaluate accurately the physical behaviors performed at home, in order to improve the computation of daily physical activity metrics. When considering long-term usage, it is crucial to distinguish between consumer- and research-grade devices. The present study employed two ActiGraph GT9X monitors, recognized as research-grade devices, in the context of a short semi-structured experiment. However, consumer-grade physical activity tracker devices used in the course of everyday life are subject to additional extrinsic limitations that can impede their ability to provide continuous monitoring. For instance, the common practice of removing watches and other wearables at home, can have significant impacts on the evaluation of physical behaviors in home settings.

Considering the current limitations of wearable activity tracker devices, smart home systems, like floor vibration monitoring technologies similar to the one employed in this study, present a suitable opportunity to enhance the self-monitoring of daily physical activity. Such systems offer a novel approach to improving the accuracy of estimating energy expenditure and the number of steps performed at home, especially when considering their integration with a 5G network composed of interconnected devices dedicated to the evaluation of daily physical activity. Smart home systems, by ensuring accurate and continuous measurements when individuals are at home, could help maintaining people interest to self-monitoring, making them a pivotal factor in promoting and sustaining active and healthy lifestyles. However, the potential widespread adoption of such systems should not only be considered from a technological perspective, but should also acknowledge the role of socio-cultural factors in shaping user acceptance and usability.

Limitations and strengths

The main limitation of the present study is that the proposed method does only assess the physical behaviors of one inhabitant at a time. Quantifying the physical behaviors of multiple individuals would require additional signal processing tools to link vibration events with the individuals generating them. Although each individual may exhibit a unique gait signature reflected in the floor vibration signal, extracting such information was beyond the scope of this study. This limitation could also be addressed by analyzing the sequences of interactions with smart and connected home furniture devices, similarly to what has already been described elsewhere [36]. Furthermore, it is important to note that the experimental *Ocha-House* used in the present study was originally designed for one single inhabitant, aligning the living environment of millions of Japanese people. The structured nature of the experimental protocol may be cited as a second limitation of the study that restrict the generalization of the observations to what may happen under free living conditions. To further evaluate the feasibility of using the floor vibration-based monitoring method, semi-structured experiments utilizing a portable breath-by-breath gas exchange analyzer could be conducted for assessing energy expenditure during longer periods of activity. A third limitation is that the external validity of the floor vibration parameter-based activity intensity prediction models (Table 2) was not tested, thus mitigating the interpretations of the comparison test preformed against the Actigraphy method. The cost of the system is also to be considered as a limitation. The present study used expensive high-sensitivity shear-type accelerometer sensors. Further studies are necessary to explore the feasibility of using cheaper accelerometer sensors similar to the ones commonly used in wearable devices. Indeed, the results of the multiple regression analyses (Table 2 and Supplementary Material 2) indicated that the floor vibration-based *step-count* and *moving-distance* parameters contributed more to the activity intensity prediction models. These two parameters may not need a high-resolution signal to be computed. Fourth, the quasi-absence of response in the *floor-count*, *step-count* and *moving-distance* parameters during *sitting and watching videos* may suggest that the floor vibration monitoring system may also be capable of evaluating sitting behaviors (Figure 4E, F, G). However, due to the structured nature of the protocol, which involves short observation windows, further interpretations regarding the accuracy of the system in predicting EE for home-based sitting activities cannot be done. Given the importance, complexity, and intricacies of sedentary behaviors that can occur at home, specific studies should be designed to understand how floor vibration monitoring systems may contribute to the objective assessment of home-based sedentary behaviors. Finally, the participants in this study are all women and exhibit relatively homogeneous characteristics in terms of age and weight. The BMI scores indicate a limited variability in physical fitness. These observations constrain the generalizability of the present results to a more diverse population. Given that age and physical fitness are recognized determinants of EE, future investigations should aim to recruit a more diverse participant sample and consider a broader spectrum of personal characteristics in the development of EE prediction models.

This study also involves several strengths and originalities. First, the results of the present experiment are in line with those of previous studies, which described a good relationship between the force exerted by an individual on the floor of a small squared 6.25 m^2 metabolic chamber equipped with force transducer and the actual energy expenditure [37-39]. They allow extending the previous observation to a different sensing technology, larger non-squared living surfaces and a wider range of activities that are usually performed at home. Another strength is that the present study is the first to compare the outcomes of a smart home system with those of research-grade activity trackers.

Conclusions

This study presents a novel floor-vibration monitoring system which can be used in smart home settings for the quantification of the physical activity at home. The hardware includes high-sensitivity accelerometers. In this case, eight sensors were necessary to cover a surface of 42 m^2. The software includes a simple data processing workflow for the computation of the *floor-count* parameter, which is a quantitative index of the floor vibrations, and the *step-count* and *moving-distance* parameters. Regression models combining the information of these three parameters showed a strong association with the actual intensities measured by indirect calorimetry for the four tested home-based activities. A significant association was also found between the *step-count* parameter computed by using the floor vibration signal and the actual number of steps. Further studies, conducted under real life conditions or using semi-structured experimental protocols, are necessary to extend the results of the present study and validate the monitoring of floor vibrations as surrogate method for evaluating of the physical behaviors at home. Considering the current evolution of 5G technologies and IoT devices, it is expected that smart home systems may contribute to a more continuous evaluation of daily physical activity.

Acknowledgements

The authors thank the women who participated in the study. NM, YO and JT would like to acknowledge all research students that contributed to the Ocha-House project in the past: Chihiro Nakajima, Saki Kaneko, Mana Akao and Mio Sasaki. This study has received research grants from the Japan Society for the Promotion of Science (Grant-in-Aid for Young Scientists-B 15K20997 directed to JT and Grant-in-Aid for Scientific Research-C 21K11335 directed to JT and YO) and from the (Japanese) Foundation for the Promotion of Precision Measurement Technology (“□□□□□□□ □□□□□□”)

Conflicts of Interest

The authors declare that there is no conflict of interest.

Abbreviations

ANOVA: analysis of variance
BMI: body mass index
EE: energy expenditure

MET: metabolic equivalent of task

Supplementary material

The calibration process is summarized and illustrated in Supplementary Material 1.
Additional results are described in Supplementary Material 2. Data used for statistics are available in Supplementary Material 3.

References

1. Warburton DE, Nicol CW, Bredin SS. Health benefits of physical activity: the evidence. CMAJ 2006; 174(6):801–809. https://doi.org/10.1503/cmaj.051351
2. Bravata DM, Smith-Spangler C, Sundaram V, Gienger AL, Lin N, Lewis R, et al. Using pedometers to increase physical activity and improve health: a systematic review. JAMA 2007;298(19):2296-304. doi:10.1001/jama.298.19.2296.
3. Shin G, Jarrahi MH, Fei Y, Karami A, Gafinowitz N, Byun A, Lu, X. Wearable activity trackers, accuracy, adoption, acceptance and health impact: A systematic literature review. Journal of biomedical informatics 2019;93:103153. https://doi.org/10.1016/j.jbi.2019.103153
4. Chaudhry UAR, Wahlich C, Fortescue R, Cook DG, Knightly R, Harris T. The effects of step-count monitoring interventions on physical activity: systematic review and meta-analysis of community-based randomised controlled trials in adults. Int J Behav Nutr Phys Act 2020;17:129. doi:10.1186/s12966-020-01020-8.
5. Vetrovsky T, Borowiec A, Juřík R, Wahlich C, Śmigielski W, et al. Do physical activity interventions combining self-monitoring with other components provide an additional benefit compared with self-monitoring alone? A systematic review and meta-analysis. British Journal of Sports Medicine 2022;56:1366-1374. doi:10.1136/bjsports-2021-105198.
6. Jia Y, Wang W, Wen D, Liang L, Gao L, Lei J. Perceived user preferences and usability evaluation of mainstream wearable devices for health monitoring. PeerJ. 2018;6:e5350. doi:10.7717/peerj.5350.
7. Shephard RJ, Aoyagi Y. Measurement of human energy expenditure, with particular reference to field studies: an historical perspective. Eur J Appl Physiol. 2012;112(8):2785-815. doi:10.1007/s00421-011-2268-6.
8. Chen KY, Bassett DR Jr. The technology of accelerometry-based activity monitors: current and future. Med Sci Sports Exerc. 2005;37(11 Suppl):S490-500. doi:10.1249/01.mss.0000185571.49104.82.
9. Mâsse LC, Fuemmeler BF, Anderson CB, Matthews CE, Trost SG, Catellier DJ, et al. Accelerometer data reduction: a comparison of four reduction algorithms on select outcome variables. Med Sci Sports Exerc. 2005;37(11 Suppl):S544-54. doi:10.1249/01.mss.0000185674.09066.8a.
10. Jeran S, Steinbrecher A, Pischon T. Prediction of activity-related energy expenditure using accelerometer-derived physical activity under free-living conditions: a systematic review. Int J Obes 40, 1187–1197 (2016). doi:10.138/ijo.2016.14.
11. Murakami H, Kawakami R, Nakae S, Yamada Y, Nakata Y, Ohkawara K, et al. Accuracy of 12 wearable devices for estimating physical activity energy expenditure using a metabolic chamber and the doubly labeled water method: validation study. JMIR Mhealth Uhealth 2019;7(8): e13938. doi:10.2196/13938.
12. Nakagata T, Murakami H, Kawakami R, Tripette J, Nakae S, Yamada Y, Ishikawa-Takata K, Tanaka S, Miyachi M. Step-count outcomes of 13 different activity trackers: Results from laboratory and free-living experiments. Gait Posture 2022;98:24-33. doi:

10.1016/j.gaitpost.2022.08.004.
13. Murphy MH, Donnelly P, Breslin G, Shibli S, Nevill AM. Does doing housework keep you healthy? The contribution of domestic physical activity to meeting current recommendations for health. BMC Public Health 13, 966 (2013). https://doi.org/10.1186/1471-2458-13-966
14. Yao L, Sheng QZ, Benatallah B, Dustdar S, Wang X, Shemshadi A et al. WITS: an IoT-endowed computational framework for activity recognition in personalized smart homes. Computing 2018;100:369–385 (2018). doi:10.1007/s00607-018-0603-z10.1007/s00607-018-0603-z.
15. GhaffarianHoseini A, Dahlan ND, Berardi U, GhaffarianHoseini A, Makaremi N. The essence of future smart houses: from embedding ICT to adapting to sustainability principles. Renewable and Sustainable Energy Reviews 2013;24:593–607. doi:10.1016/j.rser.2013.02.032.
16. Farayez A, Reaz MBI, Arsad N. SPADE: activity prediction in smart homes using prefix tree based context generation. IEEE Access 2019;7:5492-5501. doi:10.1109/ACCESS.2018.2888923.
17. Hayat H, Griffiths T, Brennan D, Lewis RP, Barclay M, Weirman C, Philip, B, Searle JR. The State-of-the-Art of Sensors and Environmental Monitoring Technologies in Buildings. Sensors (Basel, Switzerland), 2019:19(17), 3648. https://doi.org/10.3390/s19173648
18. Kientz JA, Patel SN, Jones B, Price E, Mynatt ED, Abowd GD. The Georgia Tech aware home. Proceedings of CHI '08 Extended Abstracts on Human Factors in Computing Systems (CHI EA '08, Association for Computing Machinery); 2008 Apr 5-10; New York, USA, p. 3675–3680. doi:10.1145/1358628.1358911.
19. Sevrin L, Noury N, Abouchi N, Jumel F, Massot B, Saraydaryan J. Characterization of a multi-user indoor positioning system based on low cost depth vision (Kinect) for monitoring human activity in a smart home. Proceedings of the 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 2015 Aug 25-29, Milan, Italy, p. 5003-5007. doi:10.1109/EMBC.2015.7319515.
20. Bao L, Intille SS. Activity Recognition from User-Annotated Acceleration Data. Proceedings of the Second International Conference on Pervasive Computing (PERVASIVE 2004); 2004 Apr 21-23, Vienna, Austria, Lecture Notes in Computer Science, vol 3001, p. 1-17, Springer, Berlin, Heidelberg, 2004. doi:10.1007/978-3-540-24646-6_1.
21. Helal S, Mann W, El-Zabadani H, King J, Kaddoura Y, Jansen E. The Gator Tech Smart House: a programmable pervasive space. Computer 2005;38(3):50-60. doi:10.1109/MC.2005.107.
22. Yamazaki T. The ubiquitous home. International Journal of Smart Home 2007;1(1):17–22.
23. Bahroun R, Michel O, Frassati F, Carmona M, Lacoume JL. New algorithm for footstep localization using seismic sensors in an indoor environment. Journal of Sound and Vibration 2014;333(3):1046–1066. doi:10.1016/j.jsv.2013.10.004.
24. Pan S, Bonde A, Jing J, Zhang L, Zhang P, Noh HY. BOES: Building Occupancy Estimation System using sparse ambient vibration monitoring. Proceedings of the Conference on Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2014, Apr 10, San Diego, USA. doi:10.1117/12.2046510.
25. Siio I, Motooka N, Tsukada K, Kanbara K, Ohta Y. The Ocha House and ubiquitous computing applications [In Japanese: Ocha House □□□□□□□□□□□□□□□]. Human Interface 2010;12(1):7–12.
26. Ainsworth BE, Haskell WL, Herrmann SD, Meckes N, Bassett DR Jr, Tudor-Locke C, et al. 2011 Compendium of Physical Activities: a second update of codes and MET values. Med Sci Sports Exerc 2011;43(8):1575-1581. doi:10.1249/MSS.0b013e31821ece12. PMID: 21681120.
27. 2011 Compendium of physical activities. Available at http://links.lww.com/MSS/A82

(Accessed 16 August 2023).
28. Tripette J, Sasaki M, Kuno-Mizumura M, Motooka N, Ohta Y. Monitoring floor vibrations to evaluate objectively physical activity during housework activities. Proceedings of the 3rd IEEE Global Conference on Life Sciences and Technologies (LifeTech); 2021 Mar 9-11, Nara, Japan, p. 97-101. doi:10.1109/LifeTech52111.2021.9391942.
29. Jones E, Oliphant T, Peterson P. (2001). SciPy: Open source scientific tools for Python. Available at https://scipy.org/scipylib/ (Accessed 16 August 2023).
30. Crouter SE, Kuffel E, Haas JD, Frongillo EA, Bassett DR Jr. Refined two-regression model for the ActiGraph accelerometer. Med Sci Sports Exerc 2010;42(5):1029-1037. doi:10.1249/MSS.0b013e3181c37458.
31. Seabold S, Perktold J. Statsmodels: Econometric and statistical modeling with python. Proceedings of the 9th Python in Science Conference, 2010 Jun 28 – Jul 3, Austin, USA, p. 57–61.
32. Vallat R. Pingouin: statistics in Python. Journal of Open Source Software 2018;3(31): 1026. doi:10.21105/joss.01026.
33. John D, Morton A, Arguello D, Lyden K, Bassett D. “What Is a Step?” Differences in How a Step Is Detected among Three Popular Activity Monitors That Have Impacted Physical Activity Research. Sensors 2018, 18, 1206. https://doi.org/10.3390/s18041206
34. Oshima Y, Kawaguchi K, Tanaka S, Ohkawara K, Hikihara Y, Ishikawa-Takata K, et al. Classifying household and locomotive activities using a triaxial accelerometer. Gait Posture 2010;31(3):370-374. doi:10.1016/j.gaitpost.2010.01.005.
35. Ohkawara K, Oshima Y, Hikihara Y, Ishikawa-Takata K, Tabata I, Tanaka S. Real-time estimation of daily physical activity intensity by a triaxial accelerometer and a gravity-removal classification algorithm. Br J Nutr 2011;105(11):1681-1691. doi:10.1017/S0007114510005441.
36. Chua SL, Marsland S, Guesgen H. A supervised learning approach for behavior recognition in smart homes. Journal of Ambient Intelligence and Smart Environments 2016;8:259–271. doi:10.3233/AIS-160378
37. Sun M, Hill JO. A method for measuring mechanical work and work efficiency during human activities. J Biomech 1993;26(3):229–41. doi:10.1016/0021-9290(93)90361-h.
38. Sun M, Reed GW, & Hill JO. Modification of a whole room indirect calorimeter for measurement of rapid changes in energy expenditure. J Appl Physiol 1994;76(6):2686–2691. doi:10.1152/jappl.1994.76.6.2686.
39. Chen KY, Sun M, Butler MG, Thompson T, Carlson MG. Development and validation of a measurement system for assessment of energy expenditure and physical activity in Prader-Willi syndrome. Obesity Research 1999;7(4):387–394. doi:10.1002/j.1550-8528.1999.tb00422.x

Supplementary Files

Multimedia Appendixes

Data.
URL: http://asset.jmir.pub/assets/d0e421b5182e979d9a5c4ef21a2a4ff3.xlsx

Supplementary descriptions and results about the calibration and walking trials mentioned in the main body of the article.
URL: http://asset.jmir.pub/assets/da85bf7d88d414f52352a114a8d22307.docx

Supplementary analyses and results.
URL: http://asset.jmir.pub/assets/9dac974076b0912926f850672dc6498b.docx