B. Maczák, C. G. Horváth, R. Bódizs and G. Vadai, "Revealing the Generality of 1/f Noise Based Spectral Characteristics of Human Activity Across Different Datasets," 2023 International Conference on Noise and Fluctuations (ICNF), Grenoble, France, 2023, pp. 1-4, doi: 10.1109/ICNF57520.2023.10472765.

Revealing the Generality of 1/*f* Noise Based Spectral Characteristics of Human Activity Across Different Datasets

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***Abstract*—There is substantial evidence about the scale-independent nature of human dynamics. Within the field of actigraphy, numerous findings support this claim, such as the emergence of power-law distributions and the presence of 1/*f* noise in human locomotor activity. Recently, we discovered that the spectral characteristic of human activity – which includes 1/*f* noise at frequencies greater than the daily periodicity – is universal, as both the raw acceleration of the wrist and the diverse kinds of activity signals (i.e., acceleration data compressed in varied ways) follows the same spectral nature. Here, we demonstrate that this spectral characteristic persists for daily human activity in general by analysing datasets from various sources containing activity or acceleration signals of healthy, free-living subjects.**

Keywords*—*1/f noise, actigraphy, power law, scale-free nature, human dynamics

I. Introduction

Several studies have unveiled that scale-free behaviours constitute an intrinsic part of daily human dynamics [1], including both spatial and temporal regularities. In the field of human mobility, these patterns are typically assessed through the analysis of location data [2]. However, the temporal aspects of human dynamics could also be examined using the method of actigraphy [3], which [4] quantifies the locomotor activity of the subject using a typically wrist-attached, accelerometer-based device, that is called actigraph.

Actigraphy is a versatile method employed across diverse disciplines in addition to the analysis of human dynamics, such as sleep medicine [5], psychiatry [6], or sports science [7]. Given its prevalence, one would expect it to be highly standardized. Although all actigraphs inherently measure acceleration, most of them are only capable of storing “activity values” that are derived from the relatively highly sampled (e.g., 10-100 Hz) acceleration for every consecutive timeslot (i.e., epochs, typical length of 1 minute) in a manufacturer-specific way. Fig. 1 illustrates a typical scenario for such an activity determination procedure: the raw triaxial acceleration recording is first preprocessed (e.g., magnitude calculation, normalizing or digital filtering), then cut into epochs, and converted into an activity signal using an activity metric (which is a set of nonlinear operations). However, as we already pointed out [4], the preprocessing techniques and activity metrics lack uniformity among manufacturers and vary across several scientific works, which complicates the comparison or reproduction of such studies.

Nevertheless, the scale-free nature of human daily activity has already been observed through the power-law scaling distribution of – for example – the passive periods of the motion [8], and the identification of 1/*f* noise in the fluctuations of human activity [3, 9]. In the literature, the latter is mainly carried out using Detrended Fluctuation Analysis (DFA), and rarely by examining the Power Spectral Density (PSD) of such recordings, typically for medical goals [10, 11] over a narrow timescale and frequency range, respectively. Therefore, even if the fluctuation patterns of human activity have already been partially analysed in the literature, it was difficult to draw general conclusions about the spectral nature of human activity, especially if considering the wide range of activity determination methods that may also affect it.

In our previous work [12], we overcame the limitations mentioned so far by spectrally analysing the acceleration recordings of 42 healthy individuals and also the activity signals computed from these recordings using numerous activity calculation procedures. By analysing the activity data, we revealed that human activity follows a universal spectral characteristic independent of the way of activity determination. We also discovered that even the raw triaxial acceleration of the wrist and its differently preprocessed alternatives follow the same spectral characteristic as the activity signals that are derived from the acceleration data. This full-band spectral characteristic is depicted in Fig. 2 subplot a) and contains the following components. Above a certain frequency (approx. 10^{-4} Hz) $1/f^{\alpha}$ (where $\alpha = 1$) noise can be observed for multiple decades, while the spectrum flattens at lower frequencies, and peaks corresponding to periodicities around 24 and 12 hours are visible over this white noise dominated region.

In the present work, we are extending our spectral analysis across several different datasets and groups of healthy subjects to reveal that the full-band spectral characteristic we previously identified universally describes the daily fluctuations of healthy, free-living subjects.

II. Materials And Methods

On the one hand, actigraphs available on the market mostly store activity data that are determined from the raw triaxial acceleration of the wrist. On the other, modern devices that can also store raw acceleration data are becoming increasingly common. In the latter case, it is up to the user to determine activity from the recorded acceleration retrospectively, which can be done in numerous ways, similar to how variously classical actigraphs do it in their manufacturer-specific ways during measurement.

Therefore, we aimed to include such datasets in the analysis that represent the heterogeneity of the actigraphic methodology. We have examined 2 datasets of activity signals recorded using devices of different manufacturers, 2 datasets of raw acceleration signals sampled at very different rates, and activity signals calculated from these raw recordings to assess their spectral characteristics.

A. Examined Datasets

Dataset D1 [4] originates from our measurement for psychiatric purposes utilizing a special actigraphic device developed by us. It contains 10-day-long raw triaxial acceleration signals measured at the sampling rate of 10 Hz in the ±8 g interval on the wrist of 42 healthy, free-living individuals. In our prior work [12], we assessed the spectral characteristics of daily human activity based on the analysis of these recordings, and we used it for comparison here.

Similar to D1, dataset D2 also contains acceleration data, measured on the wrist in the ±8 g interval, but in this case, we used an off-the-shelf instrument (GENEActiv Original – Activinsights Ltd., Cambridge, UK) at the sampling rate of 100 Hz. These signals were measured alongside EEG recordings as a part of a sleep research study to examine the effects of sleep deprivation. In this analysis, we examined the 4-day-long raw triaxial acceleration data of 28 healthy subjects (15 females, age: mean 24.2, SD 5.56) living their normal daily routine that was recorded before the sleep deprivation stage.

Contrary to D1 and D2, dataset D3 comprises activity recordings of 24 individuals. This data has been already used in the literature [3] to examine the scale-independent features of human activity by others, making it highly relevant to our investigations. The activity of sleep-deprived individuals and control subjects was acquired using the wrist-attached Micro Motionlogger (Ambulatory Monitoring Inc., Ardsley, NY, USA) instrument. The device employed the ZCM (Zero Crossing Mode, explained in detail later) activity metric [13] to determine an activity value for each 1-minute interval. In this analysis, we examined the 6-day-long activity data of 22 control subjects.

The machine learning research-oriented dataset D4 [14] contains activity recordings of 32 healthy control subjects, and 22 individuals suffering from depression. The data were recorded with a 1-minute epoch length using the wrist-attached Actiwatch AW4 (CamNtech Ltd., Cambridge, UK) actigraph. The activity values were determined in such a device-specific way (using a complex, integration-based metric, described in the technical appendix of the device manual [15]), that is very different from the typical methods in the literature, making the analysis of these recordings of particular interest. In this work, we analysed the 13-day-long activity data of 28 healthy subjects.

B. Activity Determination

As D3 and D4 contain activity signals recorded in different manufacturer-specific ways, and the fact that activity signals can also be calculated from the raw acceleration data of D1 and D2, it is necessary to have insight into the underlying methodology of activity determination. In one of our previous works [4], we collected and categorised the main working principles and steps [4] of how activity values can be derived from the raw acceleration.

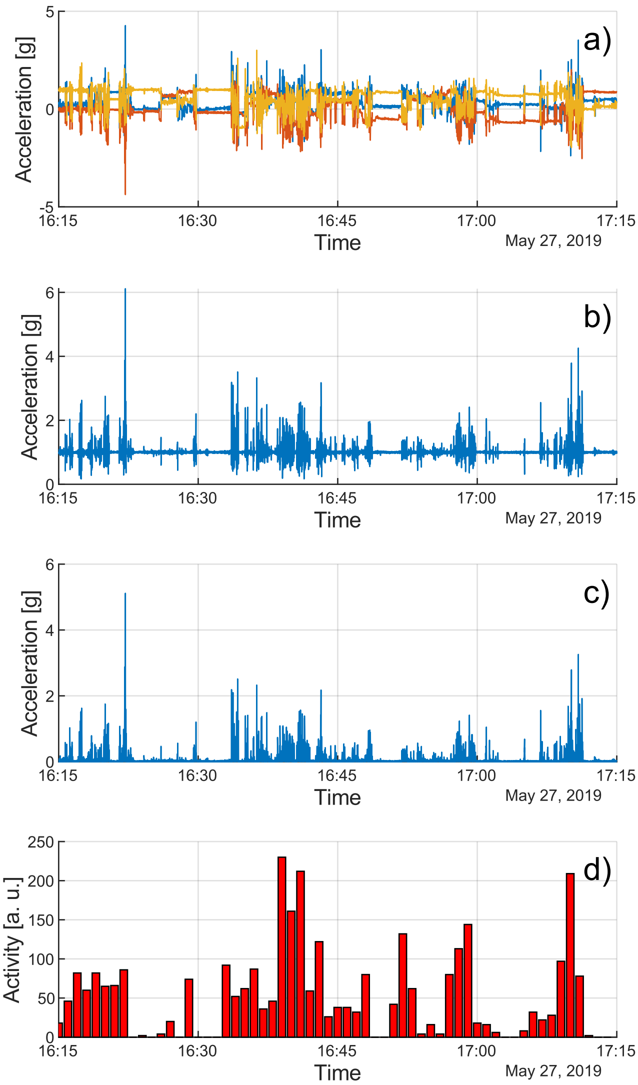

Fig. 1. Examplery 1-hour-long acceleration and activity data of a given subject of dataset D1. The x, y, and z-axis acceleration data (a) sampled with 10 Hz are illustrated with blue, red, and yellow colours, respectively. The magnitude of acceleration (b) was calculated from the raw triaxial acceleration, and then the gravity of Earth was removed by normalizing the magnitude of acceleration, which resulted in the UFNM data (c). Finally, the ZCM activity signal (d) was calculated from this normalized acceleration using epoch lengths of 1 minute.

The triaxial acceleration signal recorded by the actigraph is first subjected to a preprocessing step where the main goal is to remove the effect of Earth's gravity. This can be achieved in numerous ways, for example, by normalising or digital filtering. The preprocessed acceleration recording is then cut into epochs of equal length, and an activity value is calculated for each epoch using an activity metric. Several activity metrics exist in the literature with different working principles. For example, some use the standard deviation or the integral of the acceleration values, while other metrics are based on the level intersections of the acceleration signal. The proper combination [4] of the preprocessing techniques and activity metrics determines different kinds of activity signals. In our previous work [12], we have performed an in-depth and comprehensive spectral analysis on 7 common activity metrics combined with various preprocessing techniques.

In the current analysis, we limited to a given combination to calculate activity from the triaxial acceleration data to facilitate comparability between the examined datasets if analysing activity signals. At the preprocessing step, we chose the simplest technique of removing the effect of Earth's gravity by taking the absolute difference of the magnitude of acceleration (i.e., the length of the acceleration vectors) from 1 g. This results in the UFNM (unfiltered normalised magnitude of acceleration) data. As one of the analysed datasets (D3) of activity recordings was known to be collected using the classical ZCM activity metric, we also chose this metric to calculate activity values from the normalised acceleration data. This level intersection-based metric defines an activity value as the number of times the acceleration signal of a given epoch crosses a predefined threshold level. The correct choice of the threshold level has been discussed in our previous work [4], accordingly, the value of the threshold was set to be equal to the standard deviation of the normalised acceleration data. We used 1-minute epochs to determine activity from the acceleration datasets (D1 and D2) because both activity datasets (D3 and D4) contain minutely recorded activity values. Fig. 1 shows an illustration of how the x-, y-, and z-axial acceleration data is transformed into activity values during the procedure we use throughout the current study.

C. Spectral Analysis

In our analysis, we intended to directly compare the spectral nature of the collected recordings, for both acceleration (for D1 and D2) and activity signals (for D3 and D4, and for activity data determined from D1 and D2), to assess the universality of our prior findings about the spectral characteristics of human activity that we established by the former examination of D1.

To examine these spectral characteristics, we applied Discrete Fourier Transform (DFT) on the full-length acceleration or activity recordings of each subject and then determined their PSDs. Note that, the analysed data can vary both in terms of measurement length T and sampling rate F_s, therefore, the frequency range of the PSDs – which are bounded by frequencies of $1/T$ and $F_s/2$ – also changes between datasets and whether analysing acceleration or activity data. Then we averaged the subjects' PSDs for each dataset of activity or acceleration data, to examine their general spectral nature. The details of this ensemble-averaging procedure can be found in our previous work [12], but the principle was to divide the broadest common frequency range of the spectra into 10 logarithmic bins per frequency decade, and then take the average of the PSD values of all these spectra for each bin.

We present our results through the resulting averaged PSDs for the UFNM acceleration data of D1 and D2 (blue crosses in Fig. 2) and for the activity data of all datasets (red curves in Fig. 2 and Fig. 3), where the possible $1/f^{\alpha}$ scaling is illustrated as a trendline on log-log scales, where $\alpha = 1$.

III. Results

As depicted in Fig. 2, the PSD of D2's acceleration data follows the same characteristics that we described in the Introduction for D1 based on our previous work [12]. There is a distinct change in the shape of the spectra around 10^{-4} Hz. At higher frequencies, $1/f$ noise can be observed for multiple decades as indicated by the trendline. At lower frequencies, the PSD is flattened and exhibits white noise while peaks around the periodicities of 24 and 12 hours are visible. Examining in more detail, certain phenomena are observed to various extents in the PSDs of D1's and D2's acceleration data even if the general nature of their spectra is common. The "whitening" at lower frequencies is more observable for D1 because the longer measurement length introduces lower frequency components. In contrast, a hump between 2-3 Hz corresponding to periodic movements (e.g., walking) is more defined for D2 due to the 10 times higher sampling rate. As seen in Fig. 2, for both D1 and D2, the compression of the acceleration data into activity signals (whose PSD is depicted with red curves) results in a loss of information at higher frequencies, but at low frequencies the activity signals retain the spectral shape of the acceleration signals and follows the same spectral characteristic.

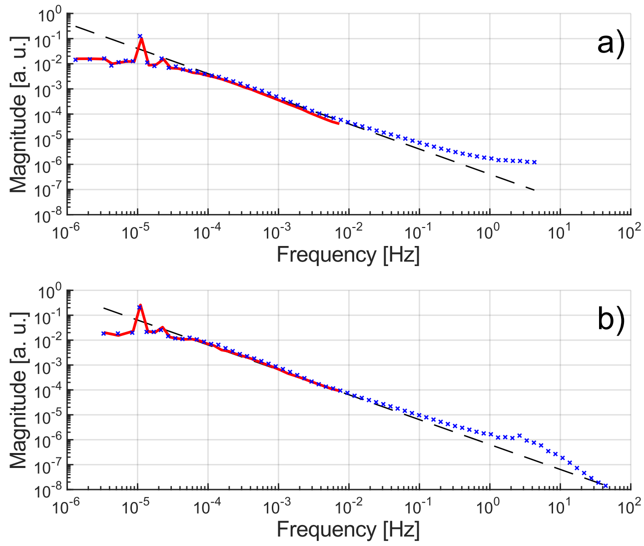

Fig. 2. The averaged PSDs of the acceleration data and the ZCM activity signals calculated from that are depicted with blue crosses and red curves, respectively, both for D1 (a) and D2 (b) datasets. The power-law scaling with an exponent of 1 is illustrated as a black dashed $1/f$ trendline.

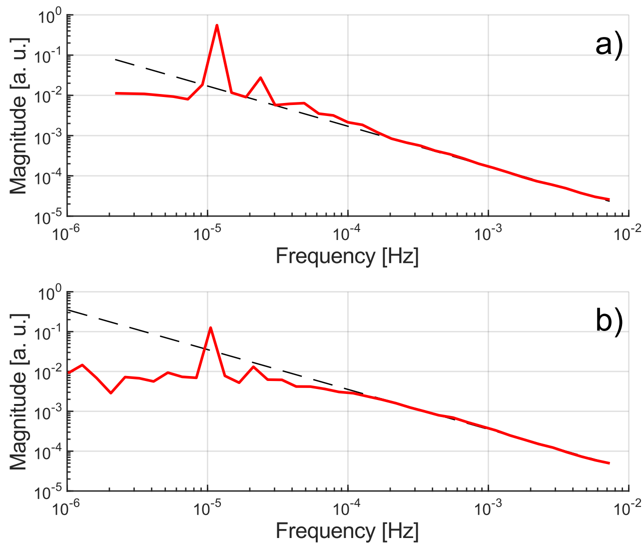

Fig. 3. The averaged PSDs of the activity signals defined in the text are depicted with red curves, both for D3 (a) and D4 (b) datasets. The power-law scaling with an exponent of 1 is illustrated as a black dashed $1/f$ trendline.

As presented in Fig. 3, both the activity signals of the D3, which had already been statistically examined in the literature, and of the unconventionally determined D4 follow this same spectral nature we described, only slight specificities can be observed. The PSD of D3 shows the most prominent peaks corresponding to the daily periodicity, which might explain why it flattens at a lower frequency as the harmonics could raise the spectrum. D4 contains the longest measurements, therefore, its PSD comprises additional lower frequency components, where its shape makes it more visible that the spectra indeed flatten at low frequencies, eventually.

Overall, we observed the same spectral features and scale-free nature [12] for the healthy subjects of all the examined datasets. Analysing the effect of age and health status could be the subject of future work. The scale independence of human activity is commonly associated with high complexity, self-similarity, and fractal nature in the literature [10]. Various bio- and neurophysiological regulatory mechanisms [16, 17] may theoretically explain this scale-free nature, while the self-organized criticality [18] could also explain the presence of $1/f$ noise. However, finding a model suitable to describe the full spectral characteristics we presented including the "whitening" at lower frequencies – which resembles what can be observed for the Matérn process [19] describing diffusion behaviour – is a challenging open question. Finding such a frequency-domain-based model may open a new perspective on the governing processes behind human daily activity and could be a step forward in understanding them, as the scale-free nature of human locomotor activity is more directly observable in the spectra than through statistical analysis [3, 8, 10]. Frequency-domain investigations are further motivated by the fact that – considering human spatial dynamics – even the minutely calculated displacement data exhibits a very similar spectral nature including $1/f$ noise – as we explored in one of our previous works [20].

IV. Conclusion

We analysed acceleration and activity signals measured using various instruments with different methodologies over several groups of healthy and free-living subjects. We demonstrated that the multi-day motion of these individuals exhibits the same spectral characteristics we previously described, including $1/f$ noise above frequencies of daily periodicity and white noise at lower frequencies. The observed spectral nature is independent of how the acceleration signals are preprocessed and how the activity values are determined, and it is identical for all four examined datasets. Therefore, we revealed the universality of these spectral properties of human activity across multiple datasets.

Acknowledgement

The authors thank Zoltán Gingl for his valuable insights and support in interpreting the results of this study.

The work of B. Maczák and G. Vadai was supported by project TKP2021-NVA-09- Project no. TKP2021-NVA-09 has been implemented with the support provided by the Ministry of Innovation and Technology of Hungary from the National Research, Development and Innovation Fund, financed under the TKP2021-NVA funding scheme.

The work of Cs. G. Horváth and R. Bódizs was supported by project TKP2021-EGA-25. Project no. TKP2021-EGA-25 has been implemented with the support provided by the Ministry of Innovation and Technology of Hungary from the National Research, Development and Innovation Fund, financed under the TKP2021-EGA funding scheme.

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