Tracking Sleep Movement Using Wearable Technologies

Observing the relationship between wearable technologies and comparing oscillation changes

QBS 126: Analysis of Densely Collected Longitudinal Data
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0. Abstract

Sleep research has made significant strides in understanding sleep's complexities and its impact on health, from early discoveries to the classification of sleep stages. This study aims to evaluate the effectiveness of wearable devices, specifically the Apple Watch Series 1 and Philips Actiwatch Spectrum Pro, in tracking sleep and identifying individual differences in sleep patterns. Using data from the Queensland University of Technology Research Data Repository, fourteen healthy adults (9 males, 5 females) wore both devices for two consecutive nights, resulting in 27 nights of data. The dataset includes timestamps, Actiwatch activity counts, sleep classification, and ENMO (Euclidean Norm Minus One), a measure of movement during sleep.

Data wrangling involved aggregating individual CSV files, inserting subject IDs, and addressing missing values using zero-inflation and median imputation methods. Exploratory analysis revealed variability in activity counts and ENMO values across subjects. Autoregression and cross-regression analyses demonstrated a significant positive correlation between the ENMO values from the Apple Watch and the activity counts from the Actiwatch. Spectral and wavelet analyses, including periodograms, identified oscillations and long-term trends in the data, indicating that both devices capture similar physical activity patterns.

The study concludes that Apple Watch ENMO values can predict Actiwatch activity counts, suggesting that both devices provide comparable information on physical activity. However, the non-stationarity and variability in the data highlight the need for personalized approaches in sleep studies. Future research should explore advanced imputation methods, improve research design by equalizing monitoring frequency, and extend observation periods to enhance the reliability and precision of activity estimates. These efforts will contribute to a better understanding of sleep behavior and the development of wearable technology for sleep research.

Introduction

Sleep research has made significant strides in understanding the complexities of sleep and its impact on health. The field has evolved from early discoveries of electrical brain activity to the classification of sleep stages, which has been foundational in identifying sleep disorders and their prevalence. Sleep is divided into stages, including rapid eye movement (REM) and non-REM sleep, each playing a crucial role in overall health and well-being. Within the non-REM stage, there are three stages, all with different lengths within the sleep cycle: N1, N2, and N3. In the N1 stage, this is when a person first begins to fall asleep and the body has not fully relaxed; brain activity however will begin to slow. As a person goes through the sleep cycle within a night, this stage will become shorter. In the N2 stage, a person is still in the "light sleep" stage, although a person will experience a drop in temperature, relaxed muscles, and slowed breathing and heart rate. By the time a person enters the N3 stage, they will experience decreases in muscle tone, pulse, and breathing rate as the body relaxes even further. Brain activity during this period also has an identifiable pattern of what are known as delta waves. This stage is considered to be very important as it is critical for restorative sleep, allowing for bodily recovery and growth, and bolstering the immune system and other key bodily processes. Lastly, within the REM cycle, brain activity picks up and the body experiences temporary paralysis. This field is vital for diagnosing sleep disorders, understanding their development, and exploring how various factors affect sleep. Sleep significantly influences attention, cognition, mood, cardiovascular health, and pain management.

To monitor sleep, polysomnography (PSG) is considered the gold standard for sleep studies, as it monitors and provides comprehensive data on brain wave activity (EEG), eye movements (electrooculogram), muscle activity (electromyogram), heart rate and rhythm (electrocardiogram), and respiration (via nasal pressure transducer and oronasal thermistor, and oxygen saturation using pulse oximetry). Although it is a valuable, non-invasive method for determining sleep continuity and architecture, PSG is expensive and not always practical. Novel approaches to objective measurement, including actigraphy, help minimize recall bias and complement subjective measures of sleep, like sleep logs or diaries. Actigraphy, an accelerometer used to observe motor activity during sleep, is often included in wearable technology so that sleep can be monitored via watch.

Recent advancements include the use of wearable technology, such as watches, to track sleep, offering new insights and changing the landscape of sleep studies. However, "the problem with wearable devices right now," says Dr. Kushida, "is that they tend to overestimate sleep, sometimes by as much as an hour" and "are not yet capable of accurately detecting different stages of sleep, such as non-REM and REM sleep. Because of our proximity to Silicon Valley, our laboratory tests a lot of these new devices, and often by the time we have finished testing one prototype, new ones have emerged. The product cycles are rapid, and the companies keep incorporating newer and newer technology. So, down the road, within about five to ten years, I think these devices will likely estimate sleep and detect sleep stages with precision."

Our research aims to evaluate the effectiveness of different wearable devices in tracking sleep and identifying individual differences in sleep patterns. Wearable data is increasingly seen as invaluable for researchers to track participants easily and increase access to measurable data. Additionally, sleep studies are beneficial for improving sleep patterns, learning more about sleep cycles, and understanding the brain during sleep. Therefore, for our research project, we will use an existing dataset from the Queensland University of Technology Research Data Repository that observes fourteen healthy adults (9 males, 5 females) who wore Apple Watches and Actiwatches

(Philips) on their non-dominant wrist for two consecutive nights. One participant forgot to charge the Apple Watch, resulting in the loss of one night of data, leaving us with 27 nights from 14 participants.

The dataset includes timestamps, Actiwatch activity counts, sleep classification, and ENMO (Euclidean Norm Minus One), a measure of movement during sleep. Each CSV file corresponds to a participant and the night of observation. There are 2453 observations per night, measured every 15 seconds. The dataset has two predictors: timestamp and activity counts, and one outcome variable: ENMO. Our research aims to answer the following questions: Are the activity counts measured by the Philips Actiwatch correlated to the ENMO variable measured by the Apple Watch? Are there identifiable cycles seen by the activity counts from the Actiwatch or the ENMO variable from the Apple Watch? We plan to use methods such as trajectory analysis, Vector Autoregression (VAR), spectral analysis, and wavelet analysis to explore these questions.

We choose to investigate the relationship between the activity counts measured by the Philips Actiwatch and the ENMO variable measured by the Apple Watch to identify any points of similarity or difference in the measuring of sleep. We also seek to find if there are identifiable cycles seen by the Philips Actiwatch and the Apple Watch.

By comparing various sensors, we seek to determine the most accurate and precise tools for sleep research, ultimately contributing to ongoing advancements in understanding sleep behavior and its implications. Additionally, the study will utilize metrics such as ENMO (Euclidean Norm Minus One) and Actiwatch values to frame the convergence and divergence in accuracy among different sensors, further enhancing the precision of sleep tracking methodologies.

1. Methods

This research will compare and determine the level of accuracy in tracking sleep between the Apple Watch Series 1 and Philips Actiwatch Spectrum Pro. The quantitative data used in this study is retrieved from the Queensland University of Technology Research Data Repository. The participants in the study comprised 9 males and 5 females who were drawn from a group of healthy adults. One of the participants forgot to charge the Apple Watch and therefore did not have data for one night. Hence, there are 27 nights of data from 14 participants in the dataset.

Since the Philips Actiwatch actigraph is considered to be the gold standard, the original study was designed to compare it with the Apple Watch in terms of accuracy, sensitivity, specificity, precision, and F1 score. Their findings suggest that the Apple Watch is sufficient for sleep evaluation, which may help expand sleep research beyond laboratory settings.

1.1 Data Description

The dataset comprises the following features: timestamp, counts of Actiwatch, wear class of Actiwatch and ENMO of the Apple Watch. The Actiwatch activity counts are derived from raw acceleration data and are obtained by performing a weighted sum through the Philips Actiware software. The ENMO variable for the Apple Watch is calculated from raw acceleration data by using the following equation.

The data is arranged in a long format, where each CSV file includes data gathered from one participant and the night they were measured (Night 1 or Night 2). There were 2453 observations made each night at 15-second intervals.

1.2 Data Wrangling

Data was cleaned as followed, before proceeding with the analysis. Initially, we aggregated individual CSV files for each participant and for each night. To differentiate between different participants and nights, a subject ID was inserted. The final merged dataset included five variables: These records consist of subject ID, time stamp, activity counts and class and Apple Watch ENMO. Next, the authors also examined the merged dataset to ensure that there were no missing values. Among all the variables, the maximum number of missing values were observed in the classification variable which had 381 missing values, followed by the Actiwatch activity counts variable which had 208 missing values and finally the Apple Watch ENMO which had 34 missing values.

To address these gaps, two imputation methods were employed. Due to the consideration of many zeros in the Actiwatch activity counts, a zero-inflation model was used. Zero-inflated models are used with count data where zero counts are more frequent than expected. In our study, the zero-inflation model splits the column into two distributions: a zero distribution and a non-zero distribution. To model the occurrence of zero activity counts, logistic regression was used in predicting the probabilities of zeros. In the case of the non-zero distribution, Poisson regression analysis was employed to manage the count data. Therefore, when applying the model to the data and estimating the necessary parameters for imputing the missing values, the maximum likelihood estimation technique was used.

For the Apple Watch ENMO and Actiware classification variables, the median imputation was applied. In particular, median imputation implies that missing values are replaced by the median of the observed values of the respective variable. This method is preferred since it does not consider outliers and provides a measure of central tendency that does not include impacts of extreme observation. In this respect, median imputation is not biased in skewing the analysis results through the imputed values as it retains the distribution characteristics of the dataset.

In addition, the timestamp was then coerced into discrete and continuous time using the lubridate function in R to make the analyses more informative and consistent.

1.3 Exploratory Analysis

Exploratory analysis was conducted to investigate the variables within the dataset and identify trends over time. The distribution of Actiwatch activity counts and Apple Watch ENMO was visualized using histograms. It was noted that the Actiwatch activity counts were zero-inflated. Additionally, trajectories by subject ID were examined to understand individual patterns and variations.

1.4 Research Question 1: Lags

To respond to the research questions, certain analytical tools were employed. To address the first research question which asks about the relationship between the activity counts recorded by the Philips Actiwatch and the ENMO recorded by the Apple Watch, autoregression and cross-regression were used. Autoregression involves estimation of a variable with its prior values which aids in the determination of temporal structures. Cross-regression investigates the existence of a causal effect between two variables while controlling for the observations of the earlier periods. Here, lags refer to relative time and not the actual time, which implies that the ENMO obtained from the Apple watch influences the subsequent changes in the activity counts recorded by Actiwatch. It helps in capturing the dynamics of the relationship between two variables over different time intervals.

1.5 Research Question 1: Modeling Oscillations

For the second research question on whether cycles can be identified from the counts of the Actiwatch and the ENMO variable from the Apple Watch, spectral analysis and wavelet analysis were employed. Spectral analysis is therefore a process of dissecting a signal in terms of its frequencies with an intention of detecting periodicity. The periodogram, a tool in spectral analysis, was employed to determine the main frequencies of a signal in terms of power. It also allows us to determine periodic changes in the data corresponding to the sleep stages.

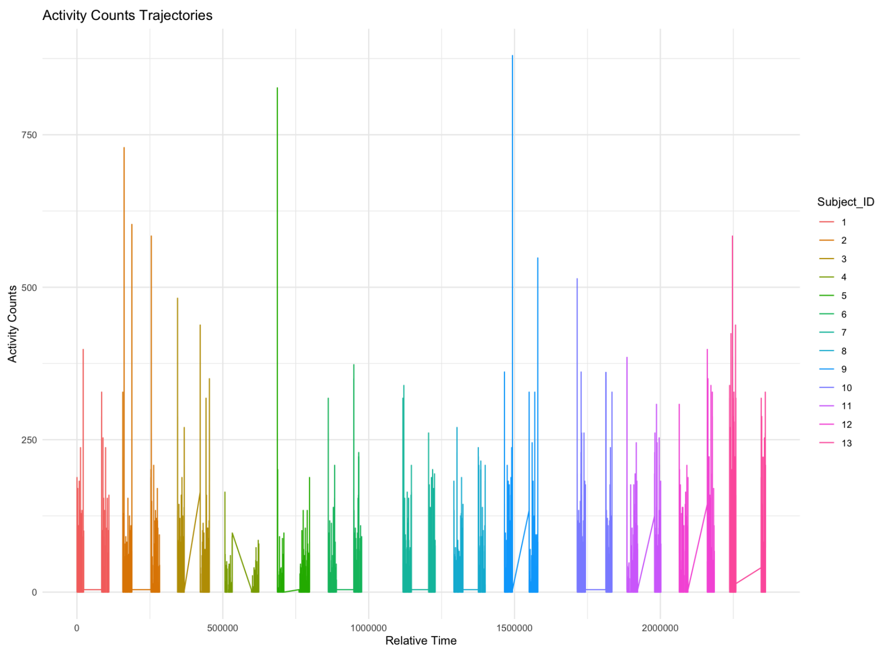
Wavelet analysis, on the other hand, allows us to measure the frequency components within time. Unlike the conventional Fourier analysis which provides frequency details the wavelet analysis provides both time and frequency details. This flexibility is crucial when working with non-stationary data such as sleep data where the frequency content may change with time. In this work, wavelet transforms were used to show and compare variation of frequency with time. The obtained wavelet power spectrum was used for identification of the intervals of intensive and low oscillations. This analysis also enables us to observe the shifts in sleep patterns and the transition from one phase to another.

From these analyses, conclusions can be drawn about the adequacy of the Apple Watch as a replacement for the Philips Actiwatch for tracking sleep. These methodological features ensure the high reliability and accuracy of the obtained results and make a worthy contribution to the creation of wearable technologies for sleep studies.

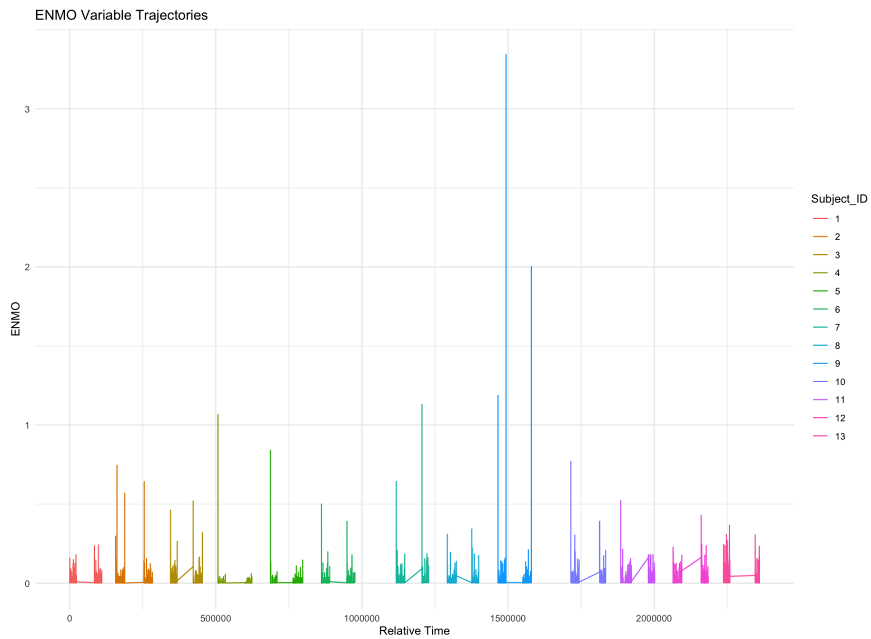
2. Results

2.1 Exploratory Analysis Results: Trajectory

The trajectory plot for activity counts displays the time proportion and activity counts of each subject. The trajectories show that subjects begin at different time points or dates, which represent the starting points of the subjects. The colors correspond to the subjects, and two bars of the same color represent night 1 and night 2 of the subject.



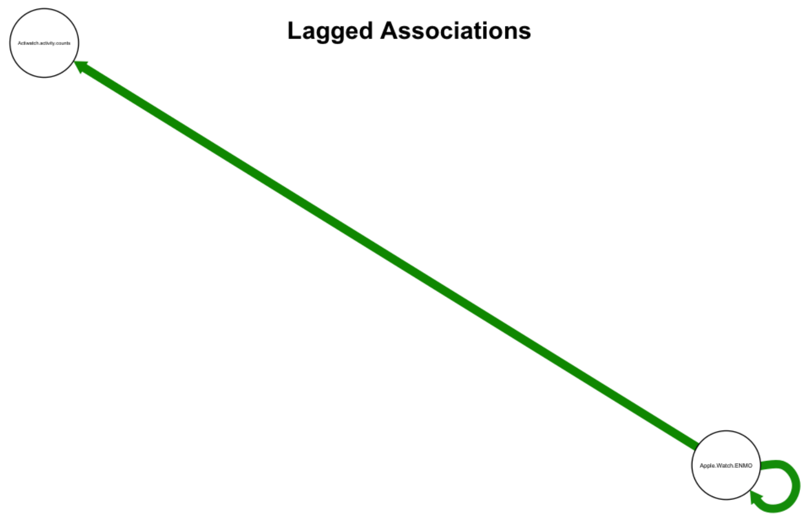
The plot shows that the activity counts are not constant across subjects and vary a lot, meaning that the activity counts are non-stationary. The large variability in the activity counts within and between subjects indicates that there exists a large variability in physical activity profiles. Likewise, the trajectory plot for the ENMO variable represents relative time against the ENMO values of each subject.



Again, just like with the activity counts, subjects begin at different time points or dates. Each bar is a different color, and if there are two bars of the same color, then those bars represent night 1 and night 2 of that subject. The ENMO variable also reveals a considerable amount of fluctuation across subjects and is therefore non-stationary. This variability in ENMO values indicates variations in the intensity and frequency of physical activity among the subjects.

2. 2 Research Question 1 Results: Lags

In addition to the lagged associations, autoregression and cross-regression results offer a deeper understanding of the connection between the ENMO and activity counts. The positive direction of the dark green line in the lagged associations diagram indicates that Apple Watch ENMO positively predicts the next time point Actiwatch activity counts.



The thicker and darker line shows that Apple Watch ENMO has a more significant autoregressive relationship with the subsequent time point than Actiwatch activity counts. This implies that ENMO is more stable over time, that is, in most of the people in the sleep study. The fixed effect coefficient of 0.551 From the results obtained on the correlation between Apple Watch ENMO and Actiwatch activity counts, it can be deduced that for every unit increase in the ENMO measurement from the Apple Watch, there will be an expected increase of 0.551 units in the activity counts determined by the Actiwatch.

from <chr>	to <chr>	lag <dbl>	fixed <dbl>	SE <dbl>	P <dbl>	ran_SD <dbl>
Actiwatch.activity.counts	Actiwatch.activity.counts	1	0.091	0.077	0.234	0.274
Actiwatch.activity.counts	Apple.Watch.ENMO	1	−0.014	0.072	0.844	0.258
Apple.Watch.ENMO	Actiwatch.activity.counts	1	0.551	0.131	0.000	0.469
Apple.Watch.ENMO	Apple.Watch.ENMO	1	0.529	0.106	0.000	0.377

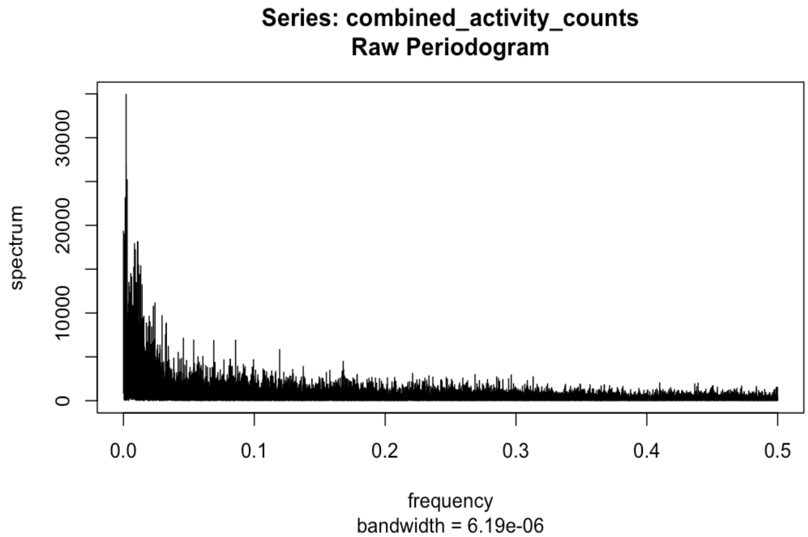
This positive sign indicates that there is a direct relationship between the two measures, meaning that higher ENMO recorded on the Apple Watch corresponds to higher activity count on the Actiwatch. This relationship is statistically significant, as the p-value is less than 0.05 (alpha level) in the present study. The random standard deviation (ran_SD) of 0 is used in this study. The value 469 suggests high variability of the data across subjects. The formulas are used in different capacities; ENMO extracts activity levels from accelerometer vectors while "Total_counts(e)" is utilized to sum up activity levels at any given time. Thus, they quantify related characteristics of physical activity and can give supplementary data in the context of sleep measurement, which is why they are highly related, r = 0. 845.

v1	v2	P 1->2	P 1<-2	pcor	cor
<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>
Apple.Watch.ENMO	Actiwatch.activity.counts	0	0	0.845	0.845

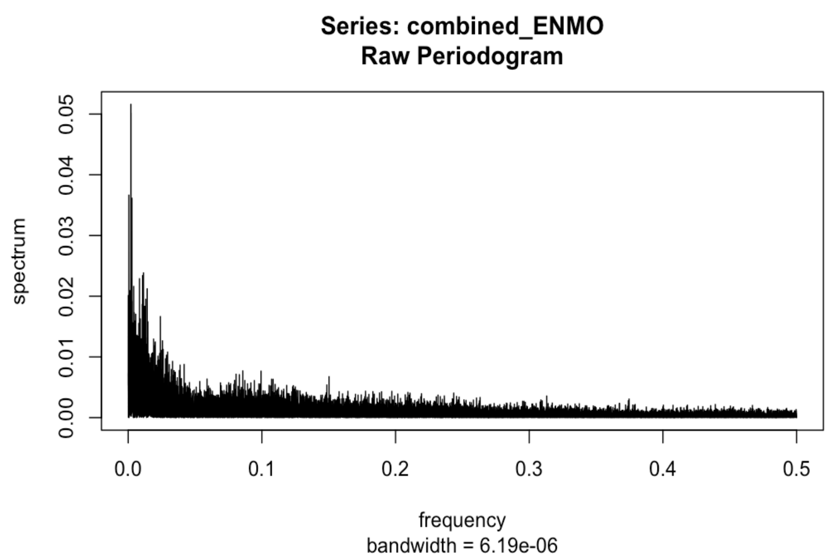
The table reveals that the Apple Watch ENMO and Actiwatch activity counts are positively and significantly correlated across the subjects with the partial correlation of 0. 845. This high value indicates that even after controlling for the effects of other independent variables in the model, there is still a significant and positive linear relationship between the random error of Apple Watch ENMO and Actiwatch activity counts.

2. 3 Research Question 2 Results

This paper also explores the modeling of oscillations for the ENMO variable obtained from an Apple Watch and the activity counts from Philips Actiwatch through periodograms, wavelet analysis, and trajectory plots. The purpose is to gain insight into the time and frequency domain attributes of these physical activity measures and their relevance to sleep research. The periodogram of the combined ENMO data shows that most of the signal power is at low frequencies with a dominant peak at the region of zero frequency.

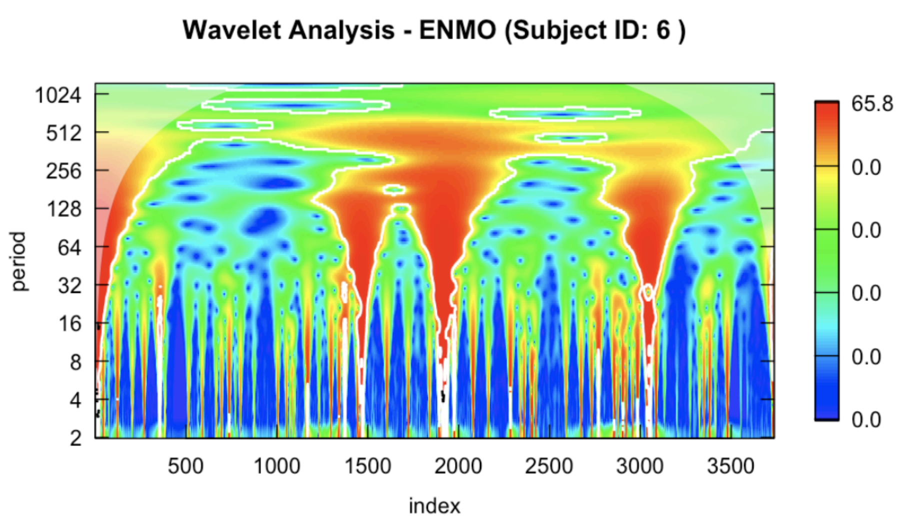


This implies that the ENMO signal mainly contains low frequency fluctuations over time, which could suggest the existence of long-term cycles or trends. High-power signal at certain times may indicate rhythmic activity patterns which may be associated with daily schedules or circadian rhythms. The sudden decrease in power when frequency increases also contributes to the dominance of slow variations in the ENMO measurements.

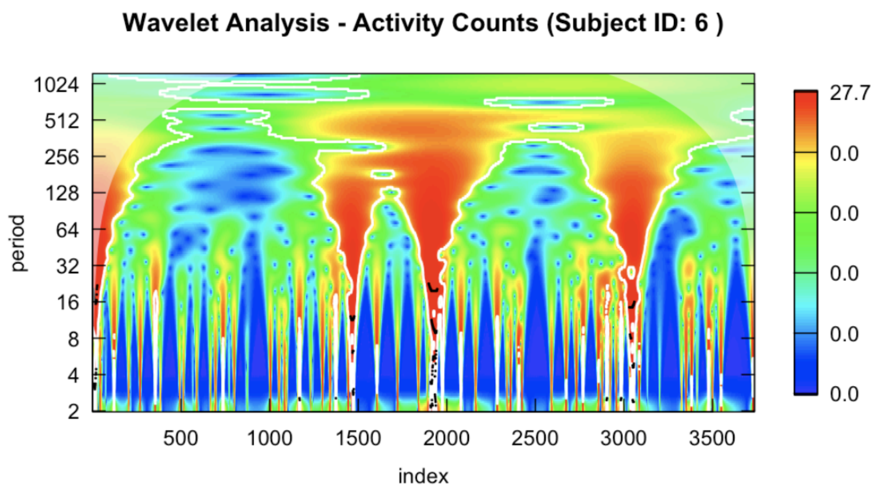


The bandwidth of the periodogram is defined as 6.190 × 10^e-06, indicating the frequency resolution of the analysis. The same may be said for the periodogram of the combined activity counts, which also indicates a high-power density at low frequencies and a maximum at zero frequency. This pattern indicates that the activity counts are mainly determined by low frequencies and long time scales. The power spectrum is a function of frequency and is observed to be decreasing with increasing frequency similar to the ENMO variable. This rapid power decrease with frequency shows that the signal is mostly composed of slow oscillations, as is the case for the ENMO variable.

Additionally, this paper presents the wavelet analysis of the ENMO variable for Subject 6, which helps to understand the temporal and frequency characteristics of the signal. The heat map indicates the power at the different periods (frequencies) and time indices. The high-power areas (shown in red) represent high oscillations at certain frequencies. The wavelet analysis visual for the ENMO variable also shows strong energy at longer periods (lower frequencies) as is evident from the periodogram.



This analysis shows that the amplitude of the signal is not constant but has cycles that occur at different time scales, indicating that the ENMO signal has long-term trends and short-term fluctuations. The wavelet analysis of activity counts for Subject 6 is similar to the pattern depicted in the ENMO analysis.



The heat map shows that there are areas of high-power (red) which suggests high oscillations. The same can be said of the activity counts data, which also exhibit significant power at longer periods, as the periodogram analysis indicated. Variability at multiple time scales is evident from the high power values at different frequencies, indicating that the activity counts signal entails long-term trends and fluctuations at shorter time scales. These oscillations are characterized by temporal stability, which means that the activity of the corresponding structures remains rather constant during the studied period.

The following observations can be made from the comparative analysis of the periodograms, wavelet analyses, and trajectory plots of the ENMO and activity counts data. The power density spectrum of both the ENMO and activity counts signals show that the power is dominated by low frequencies, meaning that the primary fluctuations in the signal are slow and sustained over long periods. This characteristic is in line with other subjects and indicates that both measures assess the same construct of physical activity. The results suggest that Apple

Watch ENMO and Actiwatch activity counts are significantly positively correlated ($r = 0.845$; $p < 0.01$). The fixed effect coefficient of 0.551 supports this relationship by indicating that the ENMO values should rise in proportion to the activity counts.

The findings show that Apple Watch ENMO values can predict Actiwatch activity counts at the next time point, and the coefficients are positive for the lag-1 relationship. This predictive capability is represented in the dark green line in the wavelet analysis, suggesting that there is a stronger auto-regressive term for ENMO. The random standard deviation is 0.469 when ENMO predicts activity counts, which shows that the two variables vary greatly from one subject to another, meaning that the correlation is not constant. Such fluctuations indicate that individual differences are the most significant factors that affect the levels of activity and their dynamics. The pattern of activity counts and ENMO variables for all the subjects shows that the measures are non-stationary, which is evident from the trajectory plots. This non-stationarity implies that the physical activity is not constant for different individuals over time, and therefore requires personalization when it comes to sleep studies. The information derived from the periodogram, wavelet analyses, and trajectory plots offers a comprehensive insight into the temporal and frequency structure of ENMO and activity counts. These measures have closely related values and similar frequency domain characteristics, which suggest that they can be used interchangeably in sleep analysis and activity assessment. The correlation between ENMO and activity counts is consistent with the hypothesis that ENMO is a valid measure of physical activity intensity. The observed variability across subjects suggests that further analysis for sleep studies should take into account the inter-subject differences in activity. In summary, the simultaneous application of periodograms, wavelet analyses, and trajectory plots provides a useful framework for analyzing physical activity data, which can help to enhance the understanding of patterns and their implications for sleep measurement and other related disciplines. The analysis of the frequency domain properties, temporal stability, and non-stationarity of the ENMO and activity counts signals provide further insight to the current literature on sleep studies and wearable technology.

3. Conclusion

In this study, we sought to understand the relationship between activity measures from two different devices: the Apple Watch and the Actiwatch - some of the most popular gadgets that are in use today in society. The results from our study suggest that the two parameters are positively correlated, meaning that if the ENMO values derived from the Apple Watch are higher, the activity counts derived from the Actiwatch will also be higher. This is to say that both devices are able to supply information on physical activity, but through different variables. However, this finding is encouraging, it also raises the question of the need to consider device characteristics while analyzing activity data.

Another variable which was incorporated into the study was the oscillatory changes in activity levels. Oscillatory changes are periodic in nature and are used to refer to fluctuations in activity levels which are periodic in nature. We also noted that these oscillations were not constant but fluctuated in most of the subjects in the study. This volatility, however, can be attributed to a number of factors. First, the oscillatory behavior of activity is non-stationary, which implies that the patterns of activity are not constant, and they change with time. This non-stationarity could be due to the fact that the stages of sleep that subjects go through during the observed time are different. This is because sleep stages are not constant and therefore activity levels are not constant either, leading to oscillation patterns that cannot be easily distinguished.

However, there are some biological, behavioral, environmental, and health factors that may have contributed to oscillatory instability. For example, genetic and neural factors, daily schedules, and environmental context might influence activity levels. Other factors that may influence the activity pattern include sleep disturbances or illnesses. The presence of these factors hinders the possibility of discrete oscillatory patterns across the subjects.

Nevertheless, this research yields insights into the features and development of activity assessment and the importance of employing wearable technology to quantify physical activity. However, it also raised questions about the desirability of seeking more effective approaches to accommodate the variability that is always present in activity data. It is therefore important to minimize this variability to enhance the validity and precision of activity estimates and to enhance the knowledge of temporal patterns of physical activity.

Based on the results of this research, the following directions for future research can be developed to further investigate the topic of activity measurement and to overcome the limitations of the present work. One of the possible fields is imputation clustering with the help of the machine learning algorithms. Imputation clustering entails categorizing the data points based on their similarity, and then applying statistical techniques to estimate missing values. It is possible to improve the quality of filling missing values in the activity datasets by using the higher level of machine learning. This can be useful in reducing the effects of gaps within the data and in improving the understanding of activity cycles. However, it is useful to consider other approaches to imputation or other strategies for dealing with missing values in the future.

For example, instead of using mean or median imputation for missing data, using time series analysis or deep learning algorithms can offer better solutions. These methods can capture the temporal dependencies in activity data and therefore give better imputations and insights into activity patterns.

There is also a need for improvement in the methods of research design. There are a few ways that can be employed in order to reduce the variability and enhance the reliability of the study. One of the possible solutions could be to equalize the frequency of monitoring for all participants. This way, we are able to reduce variation that would have been expected due to external factors and enhance the reliability of the data collected since the participants are required to monitor their sleep and activity on the same days. It is also crucial to note that increasing the observation period to more than two nights will also enable the detection of other activities, and thus the behavior of the participants will be more accurate. Another variable that should be included is the night of observation, whether it was the first night or the second night to improve organization of the data set. This variable might help in separating the dataset by night so that further analysis can be done.

Another change in research design would be to have a cutoff time for discrete time analysis, so that the number of time units is the same for all the subjects and thus will make it easier to compare data. It can also be useful in decreasing the variability of the time for activity assessment and offer a more consistent approach to assessment. Therefore, each subject's data would be divided into the same time intervals, and it would be possible to identify general patterns of activity and their variability between subjects.

In conclusion, this paper outlines the process of activity measurement and issues concerning the modeling of change in variables. As depicted in Figure 3 and Figure 4, our study shows that ENMO values obtained from the Apple Watch are positively correlated with the activity counts obtained from the Actiwatch, but the results show substantial fluctuations in activity levels. This is an area of research that should be explored in the future, in order to identify how the reliability of the measurement of activities could be enhanced. Therefore, with the assistance of these future work directions, it is possible to get deeper insight into physical activity and its tendencies, which will be helpful in improving sleep studies.

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