Comparing Wearable and Nearable Sensors Versus Polysomnography for Sleep Motor Activity Detection

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1. Introduction

Technological advancements, particularly the development of new wearable and nearable devices, are revolutionizing the domain of health monitoring and data collection and especially hold promise for advancing our understanding of sleep health [1], [2]. Consumer sleep technology (CST), encompassing portable devices like wearable sleep trackers and in-bed sensors, shows great potential for objective sleep analysis [2], [3].

These devices are particularly promising for assessing motor activity during sleep, including the detection of periodic limb movements (PLMs) [1], [4]. PLMs and generally increased motor activity during sleep are associated with various sleep and neurological disorders, such as restless leg syndrome (RLS) [5], [6]. However, arm and leg movements also occur in physiological sleep [6]. Monitoring PLMs remains important as they affect sleep quality and can indicate different disorders [4]. Reliable monitoring of sleep and motor activity during sleep can enhance our understanding of these disorders and facilitate better and earlier diagnosis [7].

The current gold standard for diagnosing many sleep disorders, including the identification of PLMs, is polysomnography (PSG) [3], [6]. PSG involves, among others, electromyography (EMG) of muscles on the extremities. To detect leg movements during sleep, mainly EMG of the anterior tibialis muscle is used [8], [9]. However, PSG has limitations: it is expensive and obtrusive, and the measuring conditions do not reflect real-world conditions [10], [11]. Furthermore, PSG is typically restricted to one or a few nights and is unsuitable for long-term monitoring [10]. Thus, there is a growing interest in new, cost-effective, and portable devices for extended health data monitoring during sleep [11].

Using comfortable and compact sensors that do not burden participants offers significant opportunities and can positively impact participant compliance [1]. Examples include wearable devices like wristbands and nearable devices like bed-based sensors [10], [11]. An accepted alternative to PSG is the use of wearable actigraphy devices, which can, for example, be worn on the wrist and use an accelerometer to measure motion in multiple directions. However, actigraphy is mainly accepted as an alternative to PSG to detect sleep-wake phases, not motor activity [2]. Nearable devices are often based on ballistocardiography (BCG). They use pressure sensors placed under the mattress to measure heart rate and movement activity [3]. A popular bed-based device is the EMFIT QS, which has also been shown to be an acceptable alternative to actigraphy for estimating sleep parameters [12], [13]. These technologies enable objective and unobtrusive measurements of various sleep characteristics [7]. Different studies that have used wearable and nearable devices to analyze motor activity during sleep will be summarized in the following paragraphs.

Actigraphy has been utilized to detect PLMs and sleep-related movement and neurological disorders in multiple studies, often comparing actigraphy to simultaneous PSG recordings [14], [15], [16]. Athavale et al. used a Naïve Bayes classifier on actigraphy measurements to distinguish between subjects with normal versus abnormal movements [14]. Brooks et al. introduced a new tool using a 6-axis inertial measurement unit to measure leg movements during sleep [8]. Kye et al. demonstrated that a foot-worn device with a 3-axis accelerometer and a 3-axis gyroscope achieves higher accuracy than devices using only an accelerometer or gyroscope individually. They also showed that a k-nearest neighbor machine learning model effectively detects PLMs [4].

Eguchi et al. proposed a different, interesting wearable device: a sock-type smart textile device with EMG electrodes to monitor PLMs. Their proposed device performed better than conventional acceleration-based wearable devices [17].

Most studies exploring contactless bed sensors used EMFIT QS devices. One study compared EMFIT QS-based sleep-wake patterns to actigraphy measurements in individuals with intellectual disabilities. They found little overlap between the two measurement methods and recommended against using EMFIT QS as an alternative to wrist actigraphy for monitoring sleep-wake phases [10]. Another study compared the periodic movement index (PMI) obtained from EMFIT QS and leg EMG. A correlation between the two was found, and they concluded that EMFIT QS sensors are suitable for screening PLMs, even when the sensors are placed beneath the patient's upper body [9]. Kholgi et al. showed that PSG and EMFIT QS measurements agreed on some sleep parameters, while there were discrepancies in others [13]. Sadek et al. suggested combining measurements from bed-based sensors and wearable devices for more accurate and robust results [11].

Sleep wearable and nearable devices have great potential to enhance our understanding of sleep and motor activity during sleep. However, there is not yet enough data on their validity, accuracy, and reliability, so they still need to be compared and used with standard PSG measurements [2].

This paper uses activity measurements from PSG and different wearable and nearable sensors recorded over one night of sleep in multiple patients. We aim to visualize and compare the activity signals from these devices to PSG measurements, which are considered the ground truth.

2. Methods

Data Collection

This study analyzed existing data from 71 patients recorded during one night of sleep. The data sources included PSG and wearable and nearable sensors. PSG data were obtained using a Somnomedics device. From the PSG measurements, only EMG measurements were used, specifically channel EMG1 and activity features calculated from an unknown EMG channel, hereafter referred to as Act PSG.

Wearable and Nearable Devices

The wearable sensor used was an Empatica E4 wristband, which includes a 3-axis accelerometer to capture motion-based activity. This wristband is a wearable wireless device designed for continuous, real-time data acquisition in daily life.

Two EMFIT QS piezoelectric mats were used as nearable sensors. These mats monitor physiological parameters during resting periods using BCG. They are placed under the mattress and record forces generated by heart contractions, breathing, and body movements. Only the activity measurements from the EMFIT QS sensors were used. One mat was placed under the patient's upper body (referred to as Emfit 05) and the other under the legs (referred to as Emfit 19).

Data Availability and Exclusions

Not all patient data included all five measurement types. Additionally, some data had to be excluded due to issues with data format and usability. Table 1 summarizes the available data for each measurement type and the corresponding number of patients included in the analysis.

Table 1 Measurement type and corresponding number of patients for whom data was available.

Measurement Type	**n (total n=71)**
EMG1	56
Act PSG	65
Empatica	61
Emfit 05	44
Emfit 19	43

Data Processing and Analysis

All data analyses were performed using Python in VS Code. The analysis was done in collaboration with Diogo Rocha (University of Fribourg). The data was loaded, inspected, and preprocessed as necessary.

A. EMG1 Data Processing

The signal envelope was calculated using the Hilbert transform. Furthermore, the signal was resampled from its original 256 Hz to 0.25 Hz to match the sampling frequency of the Emfit sensors, avoiding unnecessary processing time and power.

B. Empatica Data Processing

The original sampling frequency of 32 Hz was maintained during initial plotting. However, for cross-correlation analysis, the data was resampled to 0.25 Hz to also match the sampling frequency of the Emfit sensors. Overall activity was calculated from the raw data, which included acceleration in the x, y, and z axes. The following formula was used:

$$activity = \sqrt{x^2 + y^2 + z^2}$$

C. Act PSG and Emfit Data

The Act PSG and the two Emfit signals were not modified during preprocessing.

Visualization and Correlation Analysis

After loading and preprocessing the data, the activity measurements from all available sensors were visualized over time for each patient.

For correlation analysis, each signal was normalized using min-max normalization. Each wearable and nearable sensor signal was cross-correlated with each PSG measurement from the same patient. The signals were realigned by shifting the PSG measurement based on the maximum cross-correlation coefficient index. Pearson correlation coefficients were calculated for the aligned signals.

These steps were performed for all patients and all combinations of wearable/nearable devices (Empatica, Emfit 05, Emfit 19) with PSG data measurements (EMG1 and Act PSG). The aligned signals were then overlaid and displayed graphically for each patient. Additionally, the average correlation coefficient was computed across all patients with available measurements.

This comprehensive analysis aimed to compare the activity signals from wearable and nearable devices with the PSG measurements, considered the gold standard in sleep studies.

3. Results

Figure 1 presents examples of the visualized signals for a patient with data available from all five measurements. No example for Emfit 19 is shown, as the signal type is the same as for Emfit 05. As observed on the x-axis, not all recordings started and ended at the exact same time point. Please note that the depicted signals are relatively clean and have minimal missing data compared to some signals from other patients.

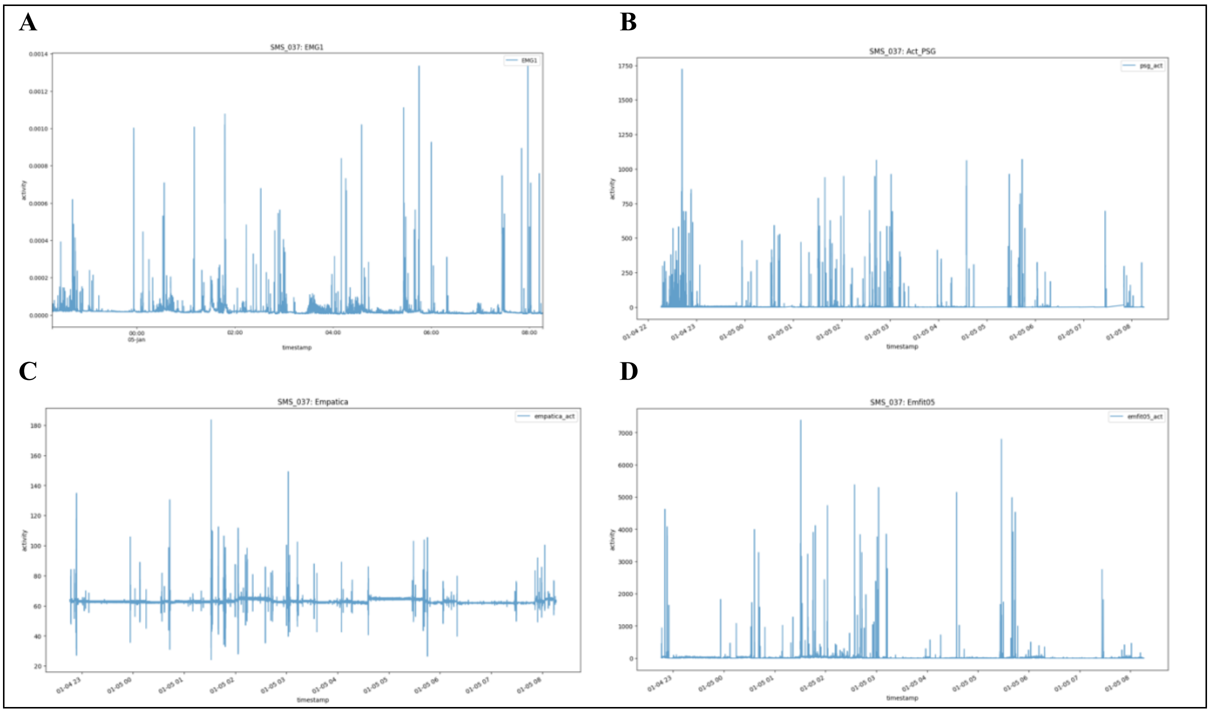

Figure 1. (A) EMG1 signal, **(B)** Act PSG signal, **(C)** Empatica signal, **(D)** Emfit 05 signal, all from patient SMS_037.

An example of the cross-correlations calculated and displayed as histograms before and after realigning the signals is shown in Figure 2. Before realignment, the highest correlation coefficient (r) occurs at a lag of -3. The PSG signal is therefore shifted by -3, resulting in the highest correlation coefficient being at 0 after alignment. It is important to note that the peak was not as distinct and high for all signals and patients as in the depicted example. Nevertheless, the signals were always realigned to have the highest correlation coefficient at 0.

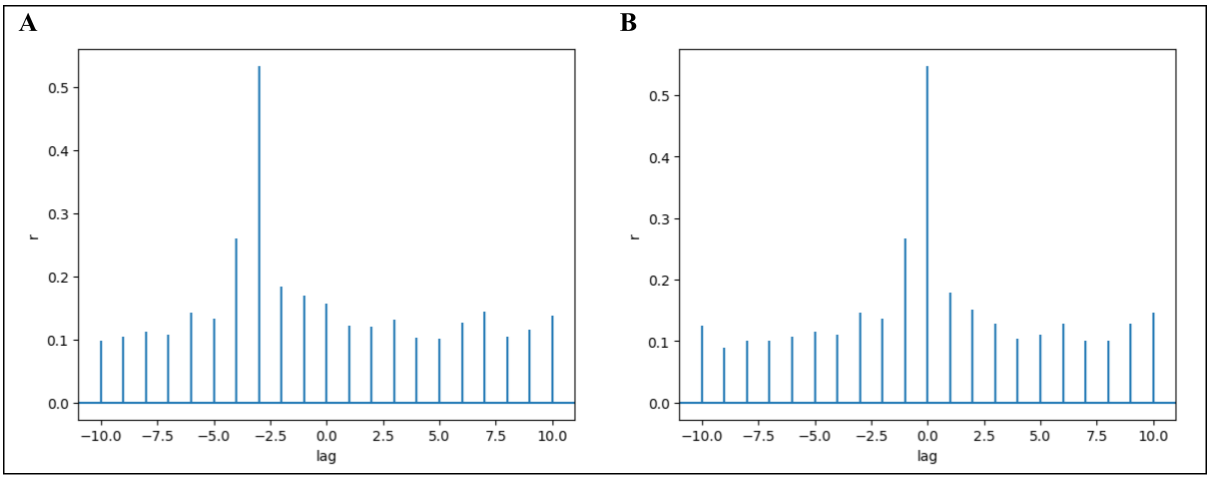

Figure 2. (A) Cross-correlation of two signals before realignment: The highest correlation coefficient occurs at -3. **(B)** Cross-correlation of the same two signals after realignment: The highest correlation coefficient is now at 0.

All combinations of wearable or nearable signals and PSG signals were overlapped for each patient. Figure 3 shows examples of the overlaid signals from two different measurements. These examples again depict relatively clean signals, while some other plots had missing data or noise at certain time points.

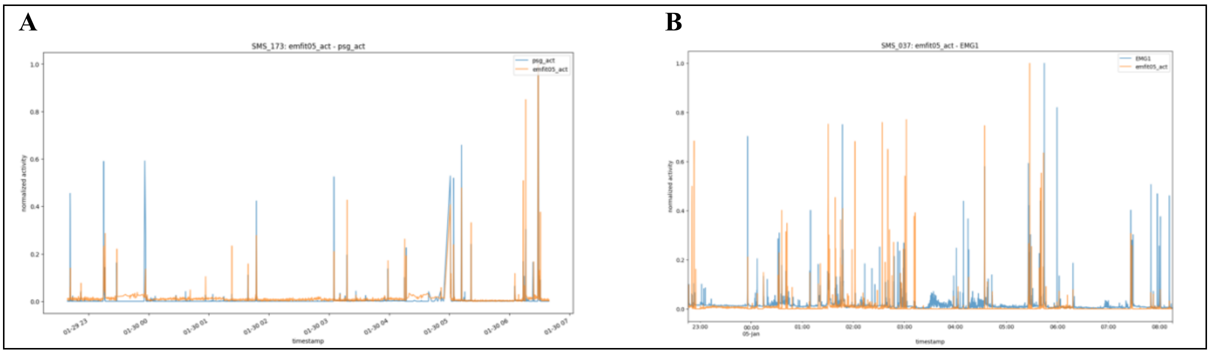

Figure 3. (**A**) An example where two signals (Emfit 05 and Act PSG) show a strong correlation (r=0.754). **(B)** An example where two signals (Emfit 05 and EMG1) show a weak correlation (r=0.277).

Table 2 summarizes the average Pearson correlation coefficients found between the three different wearable or nearable sensors and the two different PSG measurements.

Table 2. Pearson correlation coefficients between the different wearable or nearable sensors (columns) and the different PSG measurements (rows)

	Emfit 05	**Emfit 19**	**Empatica**
Act PSG	0.502	0.468	0.126
EMG1	0.203	0.216	0.021

Medium correlations were found between Emfit 05 and Act PSG (r=0.502) and between Emfit 19 and Act PSG (r=0.468). Weak correlations were observed between Emfit 05 and EMG1 (r=0.203), Emfit 19 and EMG1 (r=0.216), and Empatica and Act PSG (r=0.126). No correlation was found between Empatica and EMG1 (r=0.021).

4. Discussion

Discussion of the results

The medium correlations observed between the two Emfit sensors and the Act PSG signal indicate a moderate level of agreement between these activity recordings. Although the agreement is not very high, these correlations were the highest obtained in this study, suggesting that among the sensors analyzed, the Emfit sensors (both 05 and 19) align most closely with the Act PSG data. Previous studies have similarly shown mixed results when comparing PSG and Emfit data [13]. Rauhala et al. found a correlation between Emfit and PSG results, though they focused on the PMI rather than raw activity signals [9].

The lower correlations between the two Emfit sensors and the EMG1 channel suggest that the Act PSG data, which is already processed, captures activity more similar to the Emfit sensors than the raw EMG1 data. However, we do not know which extremities the EMG1 and Act PSG were recorded from and how Act PSG data was obtained, which could also have impacted this result.

The Empatica wristband activity showed low correlations with both Act PSG and EMG1, indicating that it may not be suitable for measuring motor activity during sleep. Therefore, the acceptability of actigraphy as an alternative to PSG could not be confirmed. However, as noted above, actigraphy has mainly been used as an alternative to PSG to detect sleep-wake phases and not motor activity [2]. Consequently, Emfit sensors should be preferred over the Empatica wristband for such purposes, given their higher correlation with PSG, the gold standard measurement.

Limitations

A significant limitation of this study is the lack of information on the specific limbs from which the EMG1 and Act PSG data were recorded. This detail is crucial, as it could influence the interpretation of correlations between these signals and the data from the other sensors.

What could also have limited our analysis is that the Empatica signal did not have a baseline of 0, which could also be observed in Figure 1. As we do not know the cause of this issue, we are unable to propose a solution to improve this.

Another limitation is that only one EMG channel was analyzed despite the PSG measurements including multiple EMG channels. This choice was made due to a limited time frame for analysis and incomplete data availability across patients. Future analyses should include all activity measurements that were recorded.

Additionally, while we aligned the PSG signal to the wearable and nearable sensor signals in this analysis, ideally, the alignment should be the other way around to maintain the integrity of the timestamps in PSG, which serves as the ground truth. However, this alignment choice is unlikely to affect the correlation results and is therefore considered a minor issue.

Future Directions

Future research should aim to correlate a broader range of wearable and nearable sensors with all available EMG recordings. This approach could reveal, for example, whether specific EMG activities, such as those recorded from the legs, correlate more closely with Emfit sensors placed under the legs. Additionally, this could confirm which wearable and nearable sensors are accurate and reliable enough to be used for analyses by themselves.

Moreover, employing machine learning techniques to automatically classify periodic limb movements could enhance the detection and diagnosis of sleep and neurological disorders. This could either be done using signals from a single sensor, or measurements from different sensors could also be combined to potentially enhance detection.

Conclusion

In conclusion, while wearable and nearable sensor technologies show promise, they require further improvement and validation against the current state-of-the-art PSG measurements. Our analysis indicates that Emfit sensors provide a more accurate measure of motor activity during sleep compared to Empatica wristbands. Therefore, Emfit sensors are recommended over Empatica sensors for more precise sleep motor activity detection. However, more research is needed to confirm these findings and to further validate those sensors.

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