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Original Article

ORIGINAL ARTICLE

Actigraphic detection of periodic limb movements: development and validation of a potential device-independent algorithm. A proof of concept study

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Abstract

Study Objectives: We propose a unique device-independent approach to analyze long-term actigraphy signals that can accurately quantify the severity of periodic limb movements in sleep (PLMS).

Methods: We analyzed 6–8 hr of bilateral ankle actigraphy data for 166 consecutively consenting patients who simultaneously underwent routine clinical polysomnography. Using the proposed algorithm, we extracted 14 time and frequency features to identify PLMS. These features were then used to train a Naïve–Bayes learning tool which permitted classification of mild vs. severe PLMS (i.e. periodic limb movements [PLM] index less than vs. greater than 15 per hr), as well as classification for four PLM severities (i.e. PLM index < 15, between 15 and 29.9, between 30 and 49.9, and ≥50 movements per hour).

Results: Using the proposed signal analysis technique, coupled with a leave-one-out cross-validation method, we obtained a classification accuracy of 89.6%, a sensitivity of 87.9%, and a specificity of 94.1% when classifying a PLM index less than vs. greater than 15 per hr. For the multiclass classification for the four PLM severities, we obtained a classification accuracy of 85.8%, with a sensitivity of 97.6%, and a specificity of 84.8%.

Conclusions: Our approach to analyzing long-term actigraphy data provides a method that can be used as a screening tool to detect PLMS using actigraphy devices from various manufacturers and will facilitate detection of PLMS in an ambulatory setting.

Statement of Significance

Periodic limb movements in sleep may have implications for health. Measurement of periodic limb movements during sleep using in-laboratory polysomnography is cumbersome and expensive; ambulatory techniques may facilitate screening of large populations efficiently and also allow for serial testing across multiple nights. This study provides an automated technique that can rapidly analyze actigraphy data and quantify periodic limb movements of sleep. One advantage of this technique is that it does not depend on a specific actigraphic device and therefore could be used in any actigraphy (regardless of manufacturer).

Key words: actigraphy; sleep; periodic limb movements; long-term monitoring; signal processing; feature extraction; polysomnography; machine learning

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Introduction

Periodic limb movements in sleep (PLMS) affect a large portion of the general population [1], but the clinical significance of this motor phenomenon remains unclear. PLMS have been reported to be associated with cardiovascular disease [2, 3], small vessel disease of the brain [4, 5], and increased mortality in renal failure [6] but their significance requires further study. PLMS usually occur during non-REM sleep and are quantified using the periodic limb movement (PLM) index [7, 8], which is defined as the ratio of total number of periodic limb movements to the total number of hours in sleep. Furthermore, PLMS can be categorized as mild (PLM index no greater than 15 movements per hour) or severe (PLM index above 15 movements per hour) [7].

Several prior studies have validated against in-laboratory polysomnography (PSG) the use of actigraphy placed on the lower extremities for the detection of PLMS (summarized in Table 1) [9–15]. Advantages of actigraphy over PSG include the opportunity to continuously record data for more than 24 hr without the need to replace sensors or batteries [9, 16–18], as well as the opportunity to evaluate patients in their natural home environments [9]. Unfortunately, the actigraphs available at any time on the market are rapidly changing, which necessitates the development of a device-independent algorithm that can detect PLMS accurately and quantify their severity.

Recently published clinical guidelines that evaluated the use of actigraphy for the detection of sleep disorders strongly recommended that clinicians should not use actigraphy instead of PSG for the evaluation of PLMS in sleep [19, 20]. The PLMS section of these guidelines was based on a review of three prior studies [10, 12, 15] whose results demonstrated that actigraphy-derived PLM indices exhibited low correlations with PLM indices derived from PSG. Although these guidelines advised against using actigraphy for the detection of PLMS, it should be noted that the conclusions were derived from studies that used limited statistical techniques (e.g., correlations and Bland Altman plots); furthermore, the guidelines only evaluated studies that reported a mean (±*SD*) PLM index attributable to actigraphy and another PLM index attributable to PSG. As a result, this approach did not

Table 1. Prior studies that have examined the use of actigraphy to detect PLMS

Authors	Actigraph	Settings and placement	Study population
Athavale et al. 2017 [9]	Philips Respironics Actical (Philips Respironics, 2015)	Sampled 32 Hz; 2 s epochs Bilateral ankles	96 consecutive patients of a sleep laboratory (52.2 ± 15.0 yr; 57 M, 39 F)
Kobayashi et al. 2014 [10]	PAM-RL	Sampled 40 Hz Bilateral ankles	41 Japanese patients with suspected restless leg syndrome (52.1 ± 16.1 yr, 14 M, 27 F)
Dias et al. 2013 [11]	Actigraph GT3X (Actigraph LLC, Pensacola Florida, USA)	Sampled 30 Hz Both legs at ankle level	2 subjects referred for a sleep study with suspect sleep apnea
Gschliesser et al. 2009 [12]	PAM-RL (IM Systems, USA); Actiwatch: (Cambridge Neurotechnology, Ltd.) DTS	Actiwatch: Sampled 32 Hz. Bilateral foot dorsa PAM-RL: Sampled 10 Hz Default settings Bilateral ankles	24 consecutive patients (57.5 ± 12 y; 18 M, 6 F); of these 10 (60.9 ± 12.0 yold; 7 M, 3 F) underwent additionalmonitoring with PAM-RL
Kemlink et al. 2008 [13]	AW-64 Actiwatch (Cambridge Neurotechnology Ltd., Cambridge UK); DTS	32 Hz resolution; 2 s epochs Bilateral ankles and dorsum of foot	40 consecutive nights in 37 adult patients withRLS and/or SRBDs (age50.8 ± 12.1 y; 29 M, 8 F)
King et al. 2005 [14]	Actiwatch (Cambridge Neurotechnology Ltd./Mini Mitter Co., Inc.); DTS	Sampling rate 32 Hz; 2 s epochs Dorsum of each foot	50 technically acceptable overnight hospital PSG (demographics unclear)
Sforza et al. 2005 [15]	PAM-RL (SOMNOmedics GmHb, Germany); DTS	Sampling rate 40/s Bilateral ankles	43 consecutive adult patients (57.6 ± 3.7 yr old; 33 M and 10 F) referred for PSG for insomnia and/or EDS;

consider the use of advanced signal analysis techniques to detect PLMS from actigraphy.

Our present research work intends to address this gap and we present a novel approach to actigraphy-based evaluation of PLMS using computer-aided analysis of actigraphy signals.

Methods

Preliminary work

In our initial set of experiments, we conducted a successful clinical validation study for the detection of PLMS using time and frequency features extracted from bilateral, short-duration (80–100 s) actigraphy signals [9]. The features were used to model a Naive–Bayes classifier, which yielded a cross-validated classification accuracy of 78.9% along with a sensitivity of 80.3% and specificity of 73.7% when classifying PLMS [9].

From our preliminary signal analyses and a review of actigraphy applications, we found that the greatest amount of human activity captured using generic accelerometry devices occurs in the 0.3–6 Hz frequency range [21–24]. The proposed algorithm in this study aims to be device-independent by employing human activity–specific filtering parameters to generic actigraphy signals. In other words, the proposed algorithm could be applied not only to the Philips Respironics Actical [25] used in our initial studies, but could also be used for other actigraphs. In this study, we apply the proposed algorithm to long-term actigraphy signals with the goal of accurately detecting PLMS and classifying their severity. The flowchart in Figure 1 illustrates a high-level description of the proposed methodology in this study.

Data acquisition and preprocessing

In the current study, bilateral ankle actigraphy data were collected from 166 consecutively consenting patients who simultaneously underwent in-laboratory PSG at a sleep laboratory. Studies were obtained for a variety of clinical indications, most commonly for assessment of sleep-disordered breathing. In-laboratory PSG (Compumedics Neuroscan, Australia) was conducted using standard recording and scoring methods [26]. The actigraphy data were acquired by placing two generic tri-axial

Findings (sensitivity, specificity)	PLMI cut-off	Analysis method	Notes
5/hr: Sn = 0.803, Sp = 0.737 15/hr: Sn = 0.841, Sp = 0.571	5/hr, 15/hr	Signal processing and machine learning. Trained and tested a Naïve–Bayes classifier using actigraphy data features, to determine PLM severity and classify patients	
r = .781 (p < .001) Sn = 0.824, Sp = 0.708	≥15/hr	Use PAM-RL software to determine PLM thresholds and compute PLM Index. Compare with PSG using statistical tests – Bland–Altman plot, Wilcoxon-signed rank test, Pearson product moment correlation and ROC curve	
Sn/Sp NRSimilarity rates = .008, .005	NR	Perform visual similarity measurements between PSG and actigraphy data to detect regions of PLM activity in actigraphy plot. Used an open source software – Movyzer which includes a similarity function to compare actigraphy and PSG.	
Sn/Sp NRActiwatch:r = 0.835, p < 0.001 PAM-RL:r = 0.939, p < 0.001	NR	Use of vendor software to detect PLMS from actigraphy data. Further comparison with PSG was done using SPSS statistics software. Tests included Wilcoxon rank sum test, Spearman correlations and Bland Altman plots	Individual subject datain supplement
AnkleSn = 0.67, Sp = 0.95 ToesSn = 1.00; Sp = 0.77	Base of the big toe 7.6/ hAnkle5/h	Manual analysis of actigraphy data using vendor software, and statistical comparison with PSG data. Spearman's correlation test) and comparative tests (pairwise sign test) were employed to analyze the data. The least square non-parametric empirical estimation was used to study relationship between parameters obtained by PSG and actigraphy.	Three patients monitored for two nights; PSG limb movements scored independent of respiratory events
5/hr: Sn = 0.906, Sp = 0.833 25/hr: Sn = 1.00, Sp = 0.971 50/ hr: Sn = 1.00, Sp = 0.978	≥5, ≥25, ≥50	Visual comparison and analysis of actigraphy data with PSG readings using vendor software and Bland–Altman analysis	SPT defined by PSG for both ACT and PSG-derived PLM indices; PSG-derived limb movements scored independent of respiratory events
Sn = 0.88, Sp = 0.76 r = 0.87, p < .0001	10/hr	Actigraphy data analyzed using vendor algorithm, and then compared statistically with PSG to determine closeness in PLM indices. Use of Pearson's correlation test and Bland–Altman analysis technique.	Individual subject data available; reported findings based on 50 studies

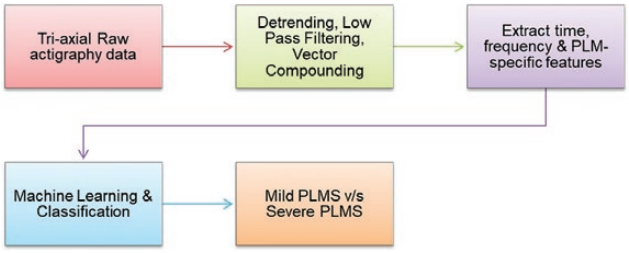

Figure 1. Algorithm flowchart.

accelerometer devices (GC Data Concepts USB Accelerometer Model X16-mini) [27] on each ankle. In comparison to the previously used Actical [25], the Model X16-mini [27] has enhanced data acquisition, storage space, universal compatibility, and a user-selectable sampling rate.

In our study, we recorded the actigraphy signals at a sampling rate of 25 Hz for the entire sleep duration of 6–8 hr. Both the PSG and actigraphy data were clipped between the "Lights off" and "Lights on" times by a registered sleep technologist, who monitored the PSG recordings during the entire night for each patient. Compared with our initial experiments [9], in the current study, we did not perform any signal truncation but rather retained the entire 6–8 hr of actigraphy signal for analysis.

As has been previously reported [4], sleep was manually staged according to criteria from the American Academy of Sleep Medicine (AASM) [26]. All studies were interpreted by a diplomate of the American Board of Sleep Medicine and scored by a registered polysomnographic technologist. Limb movements were scored according to the AASM scoring rules [26], and we used a nasal pressure transducer to exclude upper airway resistance. Limb movements were not scored within 0.5 s of a respiratory event. The PLM index for each lower extremity signal (i.e. 332 lower extremity signals for 166 participants) was subsequently used as the label for our algorithm development.

Although the currently available devices tend to sample actigraphy data at 16 Hz and/or above, the prior literature suggests that body movements are typically captured under the 6 Hz frequency band, and high-frequency noise distorts the signal around the sampling frequency [21, 22]. To address this and obtain meaningful information from the actigraphy signals, we performed the following preprocessing steps before feature extraction:

- Clipping raw actigraphy signal as per "Lights off" and "Lights on" times. No additional truncation was performed, and the entire actigraphy signal (6 to 8 hr long) was used for further analysis.
- Detrending raw signal and removal of DC (direct current) artifact from each axis-signal by subtracting individual sample values from the corresponding mean value of each axis-signal.
- Next, to remove high-frequency noise and artifacts from the signal, we passed it through a digital low pass Butterworth filter with a passband of 0.4 Hz and a stopband of 1.6 Hz, thus capturing all critical movement activity [21, 22].
- Finally, we obtained the vector magnitude [21–24] of the tri-axial signal by computing the root mean square (RMS) value of the axial components, as

$$S_v = \sqrt{x_f^2 + y_f^2 + z_f^2}.$$

Based on prior literature, when capturing and analyzing tri-axial movements, each axial component exhibits variability in amplitude, and analyzing them individually to detect a correct pattern would prove to be computationally tedious and inaccurate [21–24]. The vector magnitude represents compounded axial movements, which is better for signal analysis and pattern identification. Note that, in addition to reducing the number of computations, the vector compounded version also enhances the signal-to-noise ratio [23, 24]. In other words, the vector magnitude is a nonlinear mathematical operation that combines motor activity from three dimensions, while keeping the time-instant per movement as constant. This means that, as shown in the aforementioned equation, the vector magnitude of a three-dimensional actigraphy signal only combines the amplitudes in each direction at a given time-instant.

These preprocessing steps were applied on all actigraphy signals, for both the left and right legs, thus yielding a total of 332 individual lower extremity signals. Following this, we created two groups by prelabeling each signal as either as mild (PLM index no greater than 15 movements per hour) or severe (PLM index equal to or above 15 movements per hour), irrespective of which leg (i.e. left vs. right) each signal belonged to. Using this scheme, we obtained a total of 247 mild and 85 severe signals for our study.

Feature extraction and pattern classification

From each 6 to 8 hr long-filtered and vector-compounded actigraphy signal, we extracted the following 14 time and frequency features: mean, standard deviation, variance, RMS value, maxima, peak to peak difference, peak to RMS ratio, peak to average ratio, peak to average power ratio, median frequency, mean frequency, signal to noise and distortion ratio, band power, and periodicity index (PI). Except for the PI, the remaining 13 features were computed using standard mathematical functions available in MATLAB. The PI of an actigraphy signal was computed as [28]

$$\textit{Periodicity Index, } PI = \frac{\textit{Manually scored PLM index}}{\textit{Number of intervals between PLM events}}.$$

A valid PLM interval was defined as a period of inactivity disrupted by a limb movement [7, 8, 28]. In our study, we found the number of intervals (or periods of inactivity) in the segments between true PLMS (i.e. limb movements whose amplitude was greater than or equal to the average amplitude of the actigraphy signal) using the following relationship:

$$\text{Number of intervals between PLM events} = (\text{[Number of true limb movements]} - 1).$$

It should be noted that the computation of the PI as indicated by the aforementioned equation was based on the data available to us from the registered technologist. The absence of each candidate's limb movement measurements motivated us to estimate the number of true limb movements using the number of intervals between true PLM movements. The PI has been examined in prior studies for estimating PLM severity [28, 29]. The prior literature indicates that the PI is a stable and accurate parameter for PLM estimation [29]. Using the pre-abeling scheme described in the previous section, we grouped our feature data into mild vs. severe classes, which were then fed into a supervised Naïve–Bayes classifier [30]. The Naïve–Bayes algorithm can handle a random number of continuous or categorical (discrete)

variables, which makes it possible to reduce a high-dimensional feature-set into a simpler decision output [30]. For the reader's reference, the Naïve–Bayes tool is a machine learning technique that uses training and testing feature sets to perform pattern classification of labeled data. In this study, rather than evenly distributing the individuals with mild and severe PLMS, we distributed them in a 70–30 ratio as this would help better train the machine learning tool.

We also conducted a multiclass classification study for estimating PLM indices in various ranges. Specifically, we labeled our data into four categories, namely: (1) 247 individual lower extremity signals with a PLM index < 15 movements per hour; (2) 61 with a PLM index between 15 and 29.9 movements per hour; (3) 16 with a PLM index between 30 and 49.9 movements per hour; and (4) 8 with a PLM index ≥ 50 movements per hour. The raw MatLab code for our proposed algorithm is available in the online Supplementary Material.

Finally, we report descriptive statistics on the general characteristics, self-reported vascular risk factors, PSG parameters, and medications of our study sample, classified according to whether the individual patient had mild vs. severe PLMS (Table 2). Categorical variables are displayed as counts (%) and are compared using chi-square analyses. The normality of continuous variables was assessed using the Shapiro–Wilk test. Normally distributed continuous variables are reported as mean ± *SD* and were compared using *t*-tests. Non-normally distributed continuous variables are reported as median (range) and were compared using Mann–Whitney *U* tests.

Results

Table 2 displays the characteristics of our study population, classified as those with mild vs. severe PLMS. Patients with severe PLM indices (compared with those with mild PLM indices) were older, more likely to be male, and were also more likely to report having Restless Legs Syndrome (RLS) and diabetes. Moreover, patients with severe PLM indices had significantly greater wake after sleep onset (WASO) times and decreased stage N3 sleep. Finally, patients with severe PLM indices were more likely to be using antihypertensive, diabetic, and/or statin medications. There were no differences between the two groups in terms of use of lithium, serotonin-norepinephrine reuptake inhibitors,

Table 2. Characteristics of study participants

	Study population (*n* = 166)	PLMI <15 per hour (*n* = 107)	PLMI ≥ 15 per hr (*n* = 59)	*P* (two-tailed)
General characteristics				
Age in years, mean ± *SD*	57.4 ± 15.0	53.2 ± 15.4	65.1 ± 10.8	**<.0001**
Male, *n* (%)	96 (57.8)	55 (51.4)	41 (69.5)	**.024**
BMI, median (range)	28.6 (27.0)	28.6 (27.0)	28.9 (19.3)	.70
Self-reported RLS, *n* (%)	31 (18.7)	13 (12.1)	18 (30.5)	**.004**
Self-reported vascular risk factors				
Hypertension, *n* (%)	60 (36.1)	34 (31.8)	26 (44.1)	.12
Diabetes, *n* (%)	30 (18.1)	14 (13.1)	16 (27.1)	**0.024**
Prior stroke, *n* (%)	23 (13.9)	12 (11.2)	11 (18.6)	.19
Irregular heartbeat, *n* (%)	32 (19.3)	18 (16.8)	14 (23.7)	.28
Polysomnography parameters				
TST in minutes, median (range)	293.3 (452.0)	304.0 (445.5)	291.0 (367.5)	.09
SE, median (range)	72.9 (92.2)	74.4 (90.8)	71.2 (89.7)	.06
SOL in minutes, median (range)	14.8 (227.0)	14.5 (145.5)	15.0 (227.0)	.26
WASO in minutes, median (range)	87.3 (354.0)	68.0 (344.5)	101.0 (347.5)	**.035**
% of TST				
N1, median (range)	21.0 (90.7)	20.0 (90.7)	24.6 (60.6)	.26
N2, mean ± *SD*	48.7 ± 13.3	47.5 ± 13.1	50.8 ± 13.5	.12
N3, median (range)	9.7 (54.3)	12.8 (54.3)	5.5 (41.5)	**.002**
REM, median (range)	12.4 (37.5)	11.4 (37.5)	14.0 (31.3)	.33
REML in minutes, median (range)	118.5 (435.5)	114.0 (384.5)	132.8 (402.0)	.31
AI, median (range)	25.6 (138.1)	24.7 (138.1)	29.6 (115.6)	.97
AHI, median (range)	3.1 (98.4)	3.3 (98.4)	2.8 (70.7)	.77
Mean SaO_2, median (range)	95.0 (34.0)	96.0 (34.0)	95.0 (12.0)	.17
Lowest SaO_2, median (range)	89.0 (51.0)	90.0 (51.0)	88.0 (26.0)	.25
PLMI, median (range)	3.6 (175.3)	0.0 (14.3)	41.6 (154.3)	**<.0001**
Medications				
Antihypertensive medication, *n* (%)	73 (44.0)	41 (38.3)	32 (54.2)	**0.048**
Diabetes medication or insulin, *n* (%)	29 (17.5)	13 (12.1)	16 (27.1)	**.015**
Statin, *n* (%)	60 (36.1)	30 (28.0)	30 (50.8)	**.003**
SSRI, SNRI, TCA, or lithium, *n* (%)	35 (21.1)	20 (18.7)	15 (25.4)	.31

p-Values of < .05 are bolded.

AHI = apnea–hypopnea index; AI = arousal index; BMI = body mass index; REML = REM latency; PLMI = periodic limb movements index; SaO_2 = arterial oxygen saturation; SE = sleep efficiency; SNRI = serotonin-norepinephrine reuptake inhibitor; SOL = sleep onset latency; SSRI = selective serotonin reuptake inhibitor; TCA = tricyclic antidepressant; TST = total sleep time.

Categorical variables are reported as counts (%) and were compared using chi-square analyses. The normality of continuous variables was assessed using the Shapiro–Wilk test. Normally distributed continuous variables are reported as mean ± *SD* and were compared using *t*-tests. Non-normally distributed continuous variables are reported as median (range) and were compared using Mann–Whitney *U* tests.

selective serotonin reuptake inhibitors, or tricyclic antidepressant medications.

From the previously described feature extraction scheme, we obtained 14 features for all the 332 limb signals. This feature set was then split into 70% training and 30% testing subsets. Using these subsets, we modeled a Naïve–Bayes classifier for identifying mild and severe limb signals. The Naïve–Bayes tool yielded a high classification rate of 89% along with a sensitivity of 87.9% and specificity of 94.1%. The high accuracy of the Naïve–Bayes classifier for estimating the severity of PLMS and classifying a limb signal was further verified by cross-validating our results using the leave-one-out cross validation method. Additionally, we also benchmarked the Naïve–Bayes classification results with a linear discriminant analysis (LDA) classifier [31]. Table 3 highlights our classification results.

When we modeled a Naïve–Bayes and a LDA machine learning tool to train and classify four PLM classes (i.e. PLM index < 15, between 15 and 29.9, between 30 and 49.9, and ≥50 movements per hour), we obtained fairly high classification accuracies of 85.8% and 78.5%, respectively. Additional classification details are recorded in Table 4. These results further demonstrate that the proposed actigraphy analysis algorithm is robust and can be extended for use with multiclass classification.

Additionally, as shown in Figure 2, we also plotted the periodicity indices for all 332 signals against their respective standard deviation and signal-to-noise-and-distortion ratio (SNDR) values and observed that the PI was the most significant feature [28] for classifying test subjects based on their PLM severities. In addition, the PI showed a higher degree of variance in the lower extremities with the severe PLM indices. It should also be noted that the computation of these 14 features from each 6 to 8 hr long signal was not tedious and only took about 10 s per signal when the algorithm was executed on a Windows 7 computer.

The classification performance of the Naïve–Bayes classifier was also verified by plotting its receiver operating curve (ROC) and comparing the area under curve (AUC) to the LDA classifier. As evident from Figure 3, the AUC of the Naïve–Bayes was higher than the LDA classifier, which indicated better classification performance.

Table 3. Results for classifying PLM index less than or greater than 15

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)
Naïve-Bayes	89.6	87.9	94.1
LDA	89.2	87.3	100

Table 4. Results of multiclass classification

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)
Naïve–Bayes	85.8	97.6	84.8
LDA	78.5	86.1	84.6

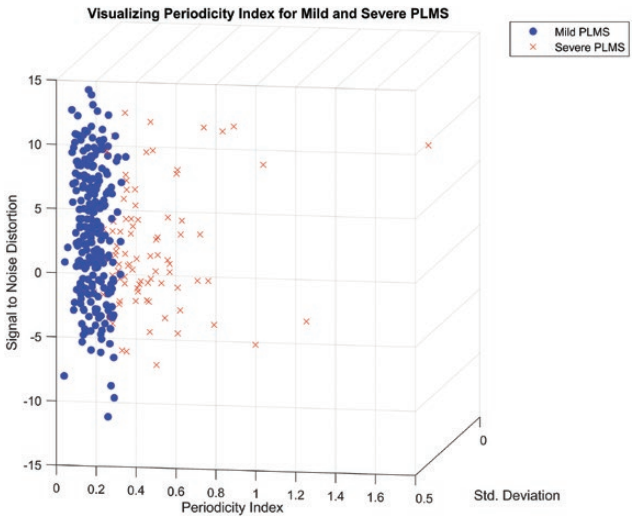

Figure 2. Plot of periodicity index vs. standard deviation and signal-to-noise distortion.

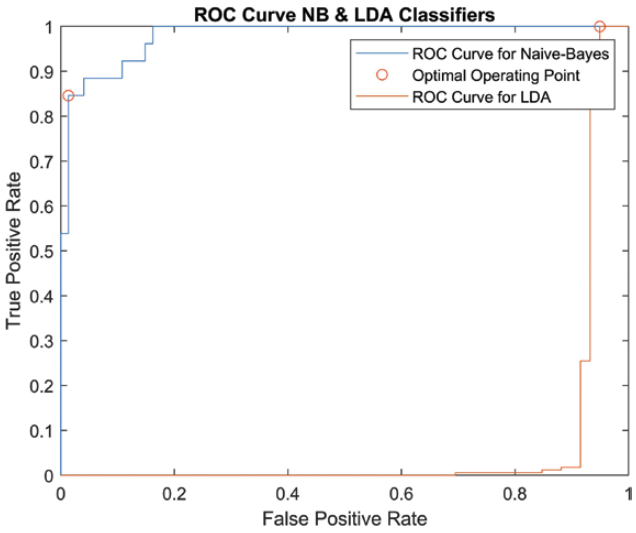

Figure 3. Receiver operating curves for Naïve–Bayes and linear discriminant analysis classifiers.

Discussion

Although several prior studies have examined the use of actigraphy to detect PLM severity [9–14, 32, 33], very few studies have examined the use of advanced signal processing methods [18, 21–24] and most studies to-date have relied on basic statistical techniques such as Pearson's correlation coefficients, *t*-tests, and Bland–Altman plots in their comparisons against PSG. Moreover, prior studies employing signal processing techniques measured their outcomes on shorter signals [18, 21–24]. It should be noted that our study did not exclude patients using certain medications or exclude those suffering from untreated sleep disordered breathing, as was done in other studies [12, 13]. We also did not need to clip our actigraphy signals, further lending support to the ease of this novel approach.

In contrast to our prior work [9], wherein we were able to perform an event-by-event comparison between the annotated PSG and actigraphy signals, in this study, considering the amount of actigraphy data acquired for each patient, we did not conduct an event-based comparison since this would have required extensive usage of sleep hypnogram data to identify different sleep stages. This would have been a tedious approach and would have negated the goal of conducting an intelligent, automated analysis of sleep actigraphy data. The intention of this study was

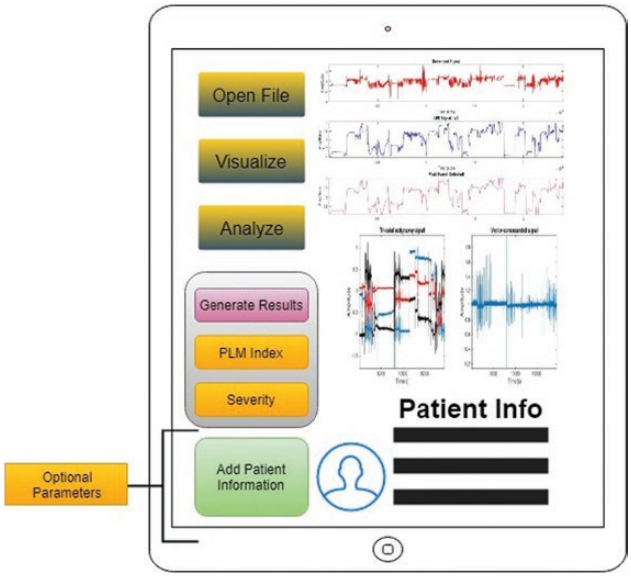

Figure 4. An example of web-based user interface of an actigraphy-based PLM estimation system.

to explore the utility of actigraphy as a screening tool to identify the severity of PLMS in an ambulatory setting.

Although our signal property tests confirmed the nonstationary nature of actigraphy data, our results demonstrated that it is possible to classify PLMS based on their severity using time and frequency domain features. This is evident from the high classification accuracies shown in Tables 3 and 4. Also, the technique proposed in this study can be applied to any actigraphy device as it is able to capture vital movement information which occurs in the frequency range of 0.3 to 6 Hz. This suggests that the proposed algorithm, in conjunction with our previous study [9], could be transformed into a generic accelerometry-based screening tool capable of identifying PLM severity across a wide spectrum of patient populations. Moreover, the Model X16 [27] is quite affordable, costing only about $100 USD, which suggests that using a generic wearable device for screening PLMS could be a potentially cost-effective approach compared with PSG.

Future work should be performed to validate the proposed algorithm using other actigraphs. Moreover, in addition to addressing the uniformity of the data set, through the availability of equal numbers of mild and severe cases, in the future we would also like to investigate the subclassification of different severities of PLMS. Future work can also explore the actigraphic correlates of PLMS presumed to be generated by different underlying etiologies (e.g. RLS, medications, and stroke). The validation and implementation of accelerometer-based sensors (such as actigraphy) has the potential to promote further home-based sleep monitoring devices and applications. Furthermore, we intend to take this study further by developing a publicly available, web-based application (Figure 4) that accepts actigraphy data as input and generates a PLM severity-based parameter based on the signal analysis conducted by our proposed algorithm.

Conclusion

In summary, we provide a novel algorithm that can accurately detect PLMS from any actigraph. Given that the actigraphs available at any time on the market are rapidly changing, our proposed device-independent algorithm has the potential to facilitate our understanding of the clinical significance of PLMS without needing to be constrained to any specific actigraphy device and provides the opportunity to study PLMS in the ambulatory setting across multiple nights of sleep.

Supplementary Material

Supplementary material is available at *SLEEP* online.

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Conflict of interest statement. This was not an industry-supported study. The authors are not involved in the development of the X16-mini and have no financial relationship with the manufacturers of the X16-mini.

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