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CLASSIFICATION OF PERIODIC LEG MOVEMENTS THROUGH ACTIGRAPHY SIGNAL ANALYSIS

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INTRODUCTION

Periodic limb movements of sleep (PLMs) are repetitive stereotyped triple flexion movements involving the great toe, ankle, and hip; they occur in repetitive sequences of four or more events at 5-90 second intervals, and last at least 0.5-10 seconds [1]. Although PLMs are associated with a wide range of medical conditions [2], emerging evidence points to a potential link with vascular disease [3]: more recent studies show that elevated PLM indices are associated with an increased risk of cardiovascular events and death [4, 5].

Actigraphy aids in the detection of PLMs and other sleep-related movement disorders. Although several previously reported actigraphs detect PLMs accurately, their signal sampling is still too infrequent for optimal detection. The Philips Respironics ® Actical™ [6] is one of the available actigraph devices which is capable of sampling at relatively high frequencies. Clinicians have been attempting to understand and diagnose neurological diseases through simultaneous recordings of EEG, EMG and actigraph signals. Although a clinician's expertise in diagnosing diseases is unquestionable, analyzing large amounts of bio-signals for hidden information requires extensive informed analysis from computer-based intelligent signal processing algorithms. These algorithms not only extract hidden information from the signal but also help in classifying between normal and abnormal test subjects based on their respective actigraph signals. The objective of this study is to develop a novel tool for analyzing sleep actigraphy signals, captured using the Actical™ [6], for estimating and classifying PLMs occurring during sleep. After pre-processing, we then extracted 14 simple time, frequency and morphology-based features from the bilateral ankle actigraphy signals. Using a Naïve-Bayes [7] classifier we obtained a classification accuracy of 78.94%, with a sensitivity of 80.26% and a specificity of 73.68%. The proposed algorithm has the potential of aiding the identification of PLMs across a wide spectrum of patient populations using the bilateral ankle actigraphy. This paper has been divided into four sections. The following three sections will describe actigraphy data acquisition, signal properties, and our proposed algorithm and classification results. We conclude this manuscript with a discussion and future works.

SIGNAL ACQUISITION AND PROPERTIES

We performed simultaneous polysomnography (PSG) and actigraphy signal acquisition on 96 consecutive patients, undergoing a routine overnight sleep study at Toronto's Sunnybrook Health Sciences Centre. Level 1, technologist-monitored in-hospital polysomnography (Compumedics Neuroscan, Australia) using standard recording and scoring methods was obtained [1]. Sleep was manually staged according to criteria from the American Academy of Sleep Medicine. All studies were interpreted by a diplomat of the American Board of Sleep Medicine and scored by a registered polysomnographic technologist [1]. The actigraphy signals were acquired using the Philips Respironics ® Actical™ [6] wearable devices placed on both ankles. This device collects signals at a sampling rate of 32Hz with an epoch of 2 seconds, which yields us an effective sampling rate of 16Hz during the polysomnography recording. The actigraphy signals provided to us by Sunnybrook Health

Sciences were also manually clipped by a research assistant according to "lights off" and "lights on" times recorded by polysomnography.

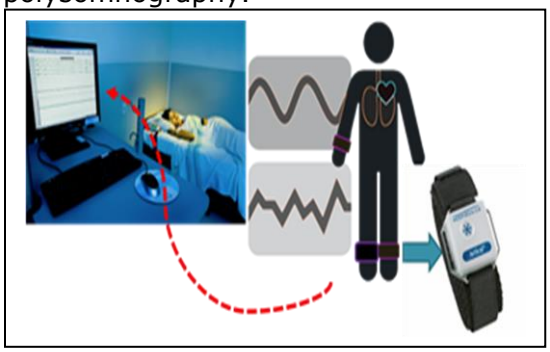

Figure 1: Actigraphy Acquisition Setup

We analyzed these clipped signals using our proposed algorithm for classifying between normal and abnormal PLM indices. The PLM index is defined as the number of Periodic Leg Movements (PLMs) detected during sleep divided by the total sleep time [1]. Figure 2 illustrates PSG and Actigraph clippings for the left leg of a sample test subject.

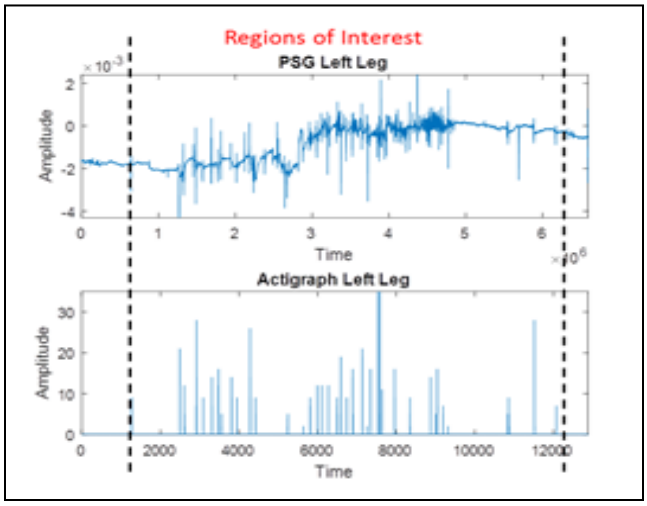

Figure 2: Actigraphy and PSG Signal Correlation

Figure 2 indicates a strong correlation between the actigraph and PSG signals with respect to the regions of interest and the leg movement activity exhibited by the test subject. As per our initial tests using standard functions in MATLAB™, we found that the actigraphy signals were non-stationary, non-Gaussian and non-linear. These type of signals can be analyzed easily using stationary time-based windows, without losing information. During the algorithm execution we further cropped the signal clippings in order to process specific regions of PLM activity. This was done in accordance with the bench-marked standard followed by clinicians [13].

SIGNAL ANALYSIS AND FEATURE EXTRACTION

Before we proceed with the methodology, the reader must note that in our algorithm, we grouped our signal data into two classes: *Normal and Abnormal*, irrespective of which leg (left/right) it belonged to. So from the 96 patients we obtained 131 *normal actigraph* signals, and 60 *abnormal actigraph* signals (one patient was missing the right actigraphy signal). The pre-labelling of the actigraph signals into Normal and Abnormal is based on the PLM indices, manually scored by the lab technician, using the following gold standard [1]: *Normal PLM Index <= 5 movements per hour, and, Abnormal PLM Index > 5 movements per hour*. We did this in order to extract robust signal features, and train the supervised classification algorithm to classify between normal and abnormal leg movements. The algorithm for this study was developed using MATLAB™.

Each individual signal (per unique extremity) was scanned for data, and its length was calculated. The signal was then truncated such that only the data recorded between the 5th and 90th seconds (which is about Sample # 80 to Sample # 1440) after the initial signal, was being processed. This was done because most of the actual PLM activity happens in this interval [13], thus making it easier for our algorithm to extract characteristic features for classification.

Table 1: Actigraph Signal Features

Actigraph Signal Features	
• Mean • Standard Deviation • Variance • Root Mean Square value • Maxima of peaks • Peak to Peak Difference • Peak to RMS ratio	• Peak to Average ratio • Peak to Average power • Median frequency • Mean frequency • Signal to Noise & Distortion ratio • Band Power • **Periodicity Index**

From these cropped signals we extracted 14 time-based [8], frequency-based and signal morphology-based features [9-16] for identifying characteristic PLM activity information. Except for the Periodicity Index, all the other features were computed using standardized signal processing functions in MATLAB™. The Periodicity index has recently become an important morphological parameter for gauging and monitoring the severity of PLMs in patients [13]. Our survey indicates that the Periodicity index [13] is a highly accurate, stable and easy to compute parameter for monitoring irregular leg movements during sleep.

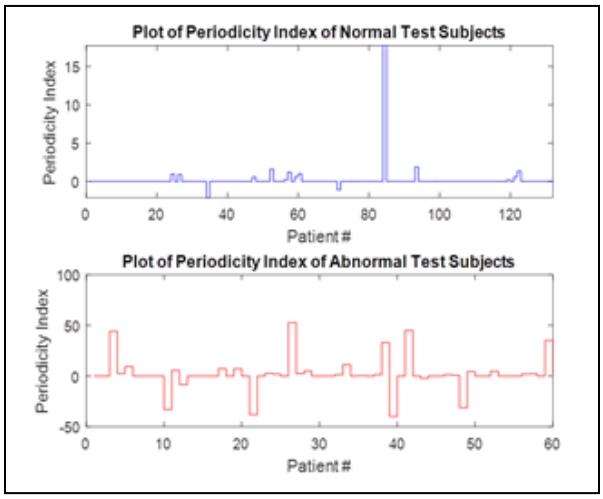

Figure 3: Periodicity Indices for Normal and Abnormal test subjects

The Periodicity Index is calculated using the number of intervals in the cropped, pre-processed signal [13]. An interval is defined as a period of inactivity which is disrupted by a leg movement. The number of intervals in the segment between true PLMs, a local maximum greater than the average peak value, is the result. The manually scored PLM index is then divided by this result to find the periodicity index [13]. Figure 3 indicates how crucial the Periodicity Index is identifying normal and abnormal test cases.

CLASSIFICATION RESULTS

Through our analysis we obtained a 14-attribute feature set for 191 actigraph signals (observations or samples). This data was further split evenly into training and testing sets, which were then applied consecutively to a Naïve-Bayes [7] classifier. We executed our algorithm in about 9.65 seconds on a Windows™ 8 computer with Intel™ Core i5 processor operating at 2.4 GHz. Table 2 highlights our experimental classification results along with Figure 4 illustrating the Receiver-Operating Characteristics (ROC curve) of the Naïve-Bayes classifier.

Table 2: Actigraphy Classification Results

Method	**Accuracy**	**Sensitivity**	**Specificity**
Naïve-Bayes [7] with all 14 Features	78.94%	80.26%	73.68%

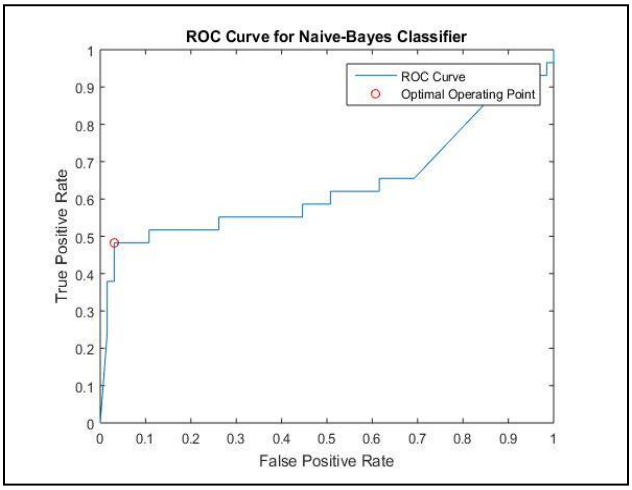

Figure 4: ROC Curve for Naïve-Bayes Classifier

Note that this system can be further trained for sub-categorizing abnormal cases into Mild (5 > PLM index <= 24), Moderate (25 > = PLM index <= 49) and Severe (PLM index > 50) [13, 15, 16]. For this, the system must be first extensively trained for binary classification, and then the resulting classifier could be used to further train using newer or previously abnormal datasets. From our experiments we found that the Naïve-Bayes classifier [7] worked best, providing considerably high

accuracy and good levels of sensitivity and specificity.

OBSERVATIONS, CONCLUSIONS AND FUTURE WORKS

From our experiments and results, we can observe that although actigraph signals are non-linear and non-stationary, their analysis can be performed by extracting simple time and frequency domain features, which yield us valuable information for classifying between normal and abnormal test cases. This being said, one must also observe that although as per Figure 2, the clipping was done well, in order to reduce human error, we can implement an automated signal clipping system which can truncate regions of interest from the actigraphy recordings. Table 2 and Figure 4 indicate that for our features, the Naïve-Bayes classifier performed really well in an exceptional execution time, and could potentially be further trained to sub-classify abnormal test cases as part of our future works. We also plan to develop a user interface so that clinicians can use this tool to enhance decision making about a patient's PLM activity and related limb movement activity.

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