Automated Detection of Sleep Disorder-Related Events from Polysomnographic Data

Hugo Espiritu
School of Engineering
and Computer Science
University of Texas at Dallas
Richardson, Texas 75080
Email: hde130030@utdallas.edu

Vangelis Metsis
Department of Computer Science
Texas State University
San Marcos, Texas 78666
Email: vmetsis@txstate.edu

***Abstract*—This work presents our effort in analyzing human biosignals collected during sleep studies, to automatically detect events related to sleep disorders. We experiment with real sleep data collected using standard Polysomnography (PSG), and we detect events of interest from EEG signals, by segmenting the signal, extracting descriptive features from each segment, and applying supervised learning for classification. Our preliminary experimental results show that the event detection goal can be successfully achieved, while our methods are general enough to be directly applied to sleep data collected using alternative, non-invasive sensors.**

***Keywords*-sleep monitoring; PSG; EEG; biosignal; segmentation; feature extraction; classification;**

I. Introduction

The National Heart, Lung, and Blood Institute estimates between 50 to 70 million Americans are currently suffering from some type of chronic sleep disorder, the vast majority of which remain undiagnosed and untreated due to the inconvenience and high costs associated with sleep studies using polysomnograms. In [1], it is mentioned that, especially in older adults, there are three sleep disorders frequently seen: sleep disordered breathing (SDB), restless legs syndrome (RLS)/periodic limb movements in sleep (PLMS), and REM sleep behavior disorder (RBD). The points mentioned above, emphasize the need for automatic, non-intrusive methods for sleep disorder recognition, that patients can use in their homes. This would not only help decrease health care costs but also increase the number of diagnosed patients. Sleep medicine is still at its early stages of development, and new technologies promise to enable new research to further understand sleep disorders and their connection with other medical conditions, and reduce costs.

The current standard in sleep disorder detection and assessment requires the patient to spend one or more nights at a specialized sleep lab attached to monitors through wired sensors connected to various parts of the human body. Such sensors include Electroencephalograms (EEG), Electromyograms (EMG), oxymeters, etc. (e.g., [2]). However, this methodology is quite inconvenient and uncomfortable for the patients due to the cumbersome wiring required for the biosignal acquisition. In addition, there is a high cost associated with a sleep test at a specialized lab [3], which includes the use of facilities and equipment, as well as, technical staff and physicians involved in the data collection and interpretation process. As a result of cumbersome sleep studies performed in sleep labs, many patients with sleep-related problems may avoid testing and go undiagnosed. Even those undergoing a full sleep study cannot be monitored over longer periods of time to assess longitudinal variations as the one or two night sleep study represents only a "snap-shot" of the sleep issues manifesting during the study.

In traditional PSG studies, events like sleep arousal, delta waves, eye movement, limb movement, obstructive apnea, SpO2 desaturation, etc., are used by sleep experts to infer various sleep disorders. These events are detected by using a combination of hardware and software tools, developed specifically for use by sleep experts, at specialized sleep labs. Especially the software developed for the analysis of biosignals collected in PSG studies, is hardware-specific, optimized at low level, and cannot be reused with different types of sensors that can collect similar biosignals. Thus, existing software solutions cannot be reused outside the lab, in combination with a set of non-invasive, of-the-shelf, plug-and-play sensors, nor can they easily adapt to the fast-changing hardware technology.

Our goal is to develop an alternative solution that allows in-home, non-invasive sleep monitoring and automated analysis of the collected data to detect, assess and monitor the progression of sleep disorders. Towards that direction we need to, first, employ a combination of non-invasive wireless sensors that have the ability to collect the necessary biosignals to successfully diagnose sleep disorders, and, second, automatically analyze the collected data and report findings in real time or in retrospect by fusing the input from the heterogeneous set of employed sensors using supervised and unsupervised machine learning and data fusion methods.

The present work contributes towards the latter of the above necessities, which is the automated analysis of raw biosignal data to detect events of interest during sleep, known to be related to a variety of sleep disorders. In our approach, we first segment the continuous, night-long signal into smaller windows. Subsequently, from each segment (window) we extract descriptive features that characterize the signal and use

those features to classify each segment as containing an event of interest or not, using supervised learning methods.

To test the effectiveness of our methods in detecting sleep disorder-related events, we use PSG data collected during real sleep studies. Even though the final goal is to use our methods to detect events from non-standard PSG sensors, the nature of the biosignals collected from the non-invasive sensors will not change, and the same methods should be possible to directly apply to signals coming from other sensors. The added advantage of using PSG data to evaluate our methods is that we can compare to existing solutions, custom-build towards the analysis of PSG signals.

Our preliminary experimental results using machine learning methods show that it is possible to automatically detect sleep disorder-related events with high accuracy. Detecting events of interest, is the first step towards detecting sleep disorders which are related to these events.

In the following sections, we first discuss the related work in sleep monitoring, as well as similar methods used to attack the problem. Subsequently, we develop our methodology for sleep-related event detection. Next, we present the experimental evaluation of our methods, and finally, conclude this work.

II. Related Work

Related research in sleep studies has focused on detecting various parameters of sleep for humans and animals as well as sleep quality and body posture recognition. [4] uses EEG and other signals and Markov modeling techniques to classify normal and abnormal human sleeping patterns. The authors in [5] evaluate classification results using spectral and nonlinear analysis for feature extraction and Quadratic Discriminant Analysis (QDA), Linear Discriminant Analysis (LDA), k-NN and Linear Regression (LR) for classification. In [6] the authors try to assess sleep quality using near-infrared video only. The authors apply a homomorphic filtering technique to tackle the problem of over exposure in the center, common in near-infrared cameras. [7] describes a new method for feature selection called multi-class f-score feature for sleep apnea classification of varying disorder degrees. The authors in [8] combine machine learning classifiers to detect real-time sleep apnea and hypopnea syndrome based on pulse and oxygen levels. In [9] a system of non-invasive sensors for detecting sleep patterns used kinect depth images and a bed pressure mat for recognizing pre-defined motion patterns and sleep postures with 90% accuracy. In [10] correspondence analysis was used to track changes in sleep patterns for individuals of varying health. [11] used machine learning algorithms for automated recognition of obstructive sleep apnea syndrome with 92% accuracy.

Even though there have been several efforts in applying technology to detect various parameters of sleep quality, to the best of our knowledge, there is no existing solution that can successfully replace PSG by providing a comprehensive alternative for sleep disorder-related event detection, which can be used to reliably assess sleep disorders outside the lab. Our work paves the way towards that direction, by developing a set of machine learning-based methods and tools that are generic enough to be used with a variety of sensors for that purpose. In the following paragraphs of this section we look further into the related work of the specific algorithmic approaches that we use in our methodology.

Signal segmentation is often a necessary preprocessing step for pattern recognition. Related work for signal segmentation includes methods specifically for segmenting biosignals for classification as well as methods for segmenting signals in general. [12] describes a method where signal segmentation and reconstruction-modeling is performed simultaneously. The equipartition principle segmentation gives signal segments that have equal errors in reconstruction selecting the most suitable model amongst wavelet, fourier and polynomial modeling to describe each segment. [13] gives a general procedure for segmenting audio signals by first extracting a sequence of short-term and mid-term feature vectors, then normalizing the extracted features to zero mean and standard deviation of one to unbias dissimilarity from overrepresenting features with large values and finally computing a dissimilarity measure for each pair of successive feature vectors to detect the local maxima where the locations of the maxima are the endpoints of the detected segments. The authors in [14] performed multi-channel EEG signal segmentation by first denoising the multi-channel signal using a FIR filter, then applying a PCA on the filtered multi-channel signal afterwards using two sliding overlapping windows for detecting signal property changes for signal segmentation and finally using the first principal component to further segment the whole set of time series. In [15] an adaptive segmentation was performed using a wavelet transform by decomposing the signal into signals with different frequency bands and then applying a nonlinear energy operator on the decomposed signals to combine the amplitude and frequency contents of the signal to find boundaries of segments. The adaptive segmentation was then applied on real EEG data to evaluate its performance on segmenting non-stationary signals.

Much work on classification of biosignals has focused on the use of EEG, EMG and ECG signals. [16] provides an overview of the applicability of the wavelet transform to EEG signals for sleep analysis and how the wavelet transform addresses the major shortcomings of the Fourier transform. Furthermore, the paper describes the application of the wavelet transform to EEG signal analysis in context of analyzing a synthetic composite signal, pattern-oriented analysis, analysis of arousal reactions, analysis of EEG in different sleep stages and analysis of an all-night sleep recording. [17] uses hidden information stored in the characteristic shapes of EEG signals to classify four types of movements. Spectral analysis of EEG signals and speech recognition techniques were used for suitable parametrization and model structure and HMMs were used for classification. [18] used a single channel EMG sensor to recognize hand gestures. Frequency domain, time domain and statistical features were extracted from the EMG signal and real-time classification with good recognition accuracy was achieved with a combination of two simple linear classi-

TABLE I
SIGNALS RECORDED BY PROFUSION PSG.

Signal #	Signal type	Sampling freq.
1	E1-M2	128 Hz
2	E2-M1	128 Hz
3	F3-M2	128 Hz
4	F4-M1	128 Hz
5	C3-M2	128 Hz
6	C4-M1	128 Hz
7	O1-M2	128 Hz
8	O2-M1	128 Hz
9	ECG1-ECG2	128 Hz
10	Chin1-Chin3	128 Hz
11	Chin2-Chin1	128 Hz
12	M1	128 Hz
13	Snore	128 Hz
14	Pulse	16 Hz
15	CPAP Flow	16 Hz
16	Alt Snore	128 Hz
17	Alt Nasal Press	16 Hz
18	Thermister	32 Hz
19	Alt Thor	32 Hz
20	Alt Abdo	32 Hz
21	Sum	32 Hz
22	SpO2	16 Hz
23	Leg/R	128 Hz
24	Leg/L	128 Hz
25	Tidal Vol	16 Hz
26	Leak	16 Hz
27	CPAP Press	64 Hz
28	Position	16 Hz

fiers in decision level fusion. [19] used an HMM approach for online beat segmentation and classification of electrocardiograms by means of waveforms modeling, multichannel beat segmentation and classification and unsupervised adaptation to the patient's ECG.

III. METHODOLOGY

A. Data

The data used in our experiments were collected during sleep study sessions, at the Texas State Sleep Center, using the Compumedics ©Profusion PSG 3 and were converted to anonymized format for research purposes. Profusion PSG allows the recording of 28 different physiological signals, at different sampling rates, as listed in (Table I). Signals #1-8 are electroencephalogram (EEG) signals, signal #9 is the electrocardiogram (ECG) (combination of two electrodes), signals #10 & 11 are electromyography (EMG) signals from the chin, signal 12 is a mastoid region reference signal, signals #13 & 16 monitor snoring, and signals #23 & 24 are EMG signals from the legs. All the above signals are sampled at 128 Hz.

Profusion PSG, besides facilitating signal recording and exporting into textual format for analysis, provides visualization of the raw signals, for visual assessment by the clinical expert, as well as annotations of events that can be automatically detected from the PSG data, e.g. sleep stage, limb movement, respiratory events, etc. Fig. 1 shows a snapshot of a 30-second epoch, of a patient in NREM 3 sleep stage, as recorded in a sleep study. The Profusion software and the sensors used to collect the signals, come as a package, and the signal analysis capabilities of the software have been built and optimized for these sensors.

The event detection annotations provided by Profusion are trusted by sleep experts to assess sleep disorders, hence, we consider them accurate enough to be used for training and testing our more general, machine learning-based event detection methods. In this work, we use the provided annotations as the *ground truth* for the evaluation our methods. Fig. 2 shows sample annotations provided by Profusion for an EEG signal including an arousal event, and an EEG and an EMG signal including a leg movement event. In this work we used the data from a full night sleep study (8 hrs, 25 mins) of one patient. Our experimental results are limited to sleep arousal and leg movement events. The dataset included 121 arousal events, 342 right leg movement and 359 left leg movement events.

B. Signal Segmentation

Signal segmentation is often a necessary preprocessing step for classification. After the signal has been segmented into smaller windows, features can be extracted from each window (segment) and be used for event detection. In this work we experimented with, and compared, two different approaches for the segmentation of the EEG signals:

1) A fixed-size window segmentation with a 30 second window size and two second overlap.
2) An adaptive, variable-length signal segmentation technique described in [20].

The fixed-size window segmentation approach is obviously easier to implement, but it has the disadvantage that the window size may be much larger than the actual duration of the event of interest. As a result, the features extracted and used for classification may include a lot of irrelevant information, which can hurt the event detection accuracy.

The adaptive, variable-length segmentation attempts to segment the signal into regions where there is a detectable change in the signal pattern, assuming that this change signifies an event of some kind. The actual type of event can be recognized at a later stage. As our experimental results show, this results in higher recognition accuracy.

Analysis of long-term EEG signals requires that the signals be segmented into stationary-like epochs, which can be accomplished by taking into account statistical properties of the signal such as amplitude and frequency. Real world time series data is typically non-stationary and the extraction of useful information from the observed time series necessitates first removing as much noise as possible from the signal with the use of a filter or smoother when pre-processing the signal. The adaptive signal segmentation technique first filters the signal to attenuate short-term variations to allow for a more reliable segmentation and then segments the filtered signal based on changes of the amplitude and frequency using a modified version of the Varri method. The adaptive segmentation required the use of the first principal component

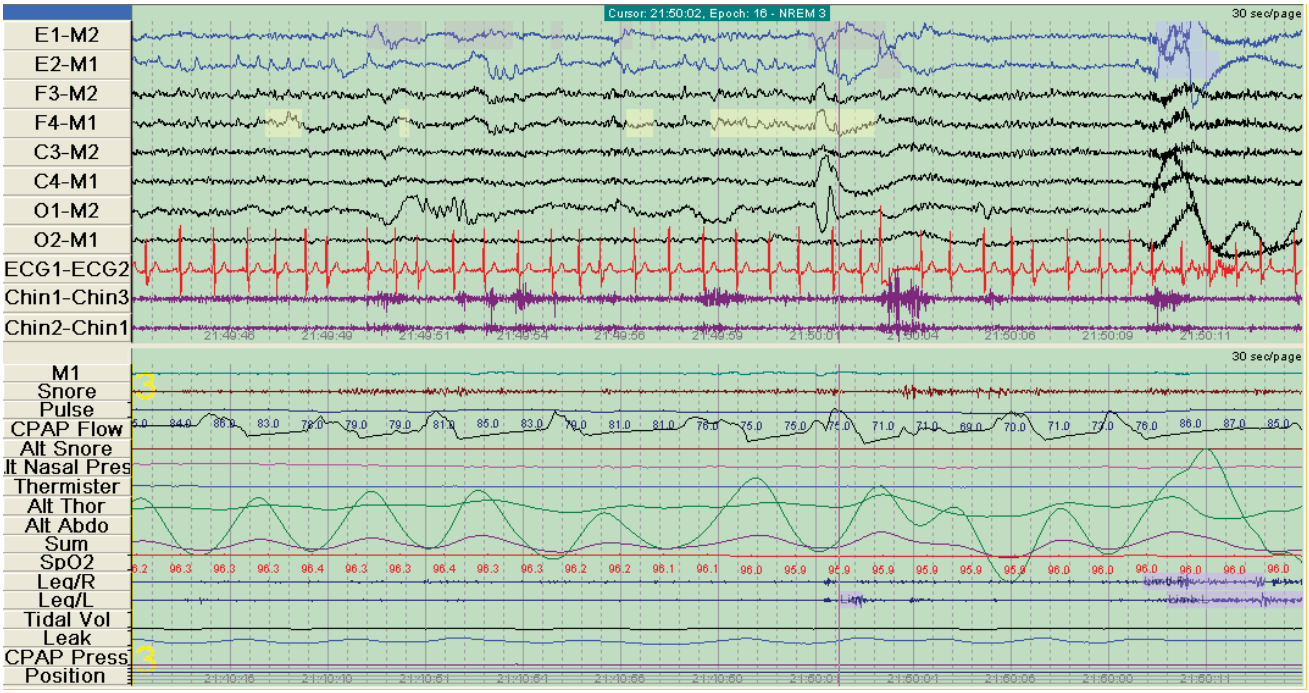

Fig. 1. A 30-second epoch visualization of the signals recorded by Profusion PSG 3 software, during a sleep study.

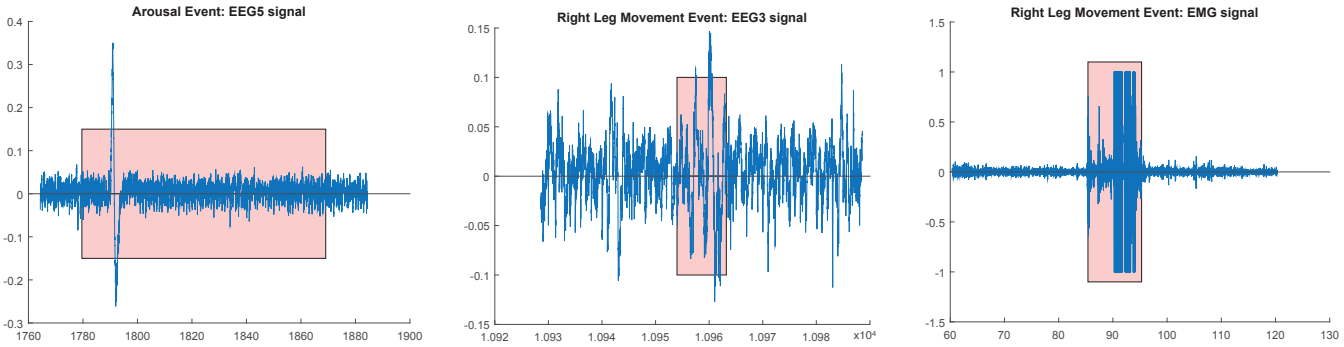

Fig. 2. **Left:** Example of an arousal event (EEG signal). **Middle:** Example of a leg movement event (EEG signal). **Bottom:** Example of a leg movement event (EMG signal).

for multi-channel EEG signal segmentation as described in [14] to allow the same number of windows for each signal, which was needed for the classification step (Fig. 3).

The Savitzky-Golay filter is a useful tool for denoising and smoothing signals where the post-filtered signal contains less noise than the original signal and displays less distortion than other simpler techniques such as the moving average filter. The Savitzky-Golay filter is defined as a weighted moving average with weight given as a polynomial of specific degree. The coefficients of a Savitzky-Golay filter, when applied to a signal, perform a polynomial P of the degree k, is fitted to N = $N_r + N_l + 1$ points of the signal, where N is the window size and N_r and N_l are signal points on the right and signal points on the left of a current signal point, respectively. The main advantage of the Savitzky-Golay filter is that it tries to preserve the features of times series such as its relative minima and maxima, which is an important issue for signal segmentation. Unlike wavelets, these filters don't have shifting effects after filtering the signal which is a vital characteristic to detecting true boundaries of epochs. For the EEG data, we have used an an order 3 polynomial Savitzky-Golay filter and a frame size of 51 samples.

Since the segmentation of multi-channel signals should be performed over all channels, in most cases it is important to extract information present in all parallel time series at first. A principal component analysis can be used to do this by reducing the dimension of a matrix $E_{N,M}$ which represents multichannel data, where the N is the number of observations and M is the number of EEG channels. The multichannel EEG matrix can be transformed into a new matrix that contains channels with decreasing variance by first computing the principal component coefficients, $P_{M,M}$, of $E_{N,M}$ and then

using the matrix product $Y_{N,M} = E_{N,M} \cdot P_{M,M}$. To enable a single segmentation of all eight EEG signals, the first principal component, that is the first column of $Y_{N,M}$, was used for the multi-channel segmentation.

In the modified Varri method two sliding windows are used. This method relies on a combination of a frequency measure estimated by the sum of the difference of consecutive signal samples and amplitude values of the signal in relevant windows as follows:

$$A_{dif} = \sum_{k=1}^{l} |x|$$

$$F_{dif} = \sum_{k=1}^{l} |x_k - x_{k-1}|$$

where l and x_k are the window length and the k^{th} signal point, respectively. Then, the measure difference function, G, is defined as:

$$G_m = A_1 |A_{dif_{m+1}} - A_{dif_m}| + F_1 |F_{dif_{m+1}} - F_{dif_m}|$$

where m is the number of the window; A_1 and F_1 are constant coefficients which change in various applications. Local maxima in the G function, above a threshold that is defined before, specify boundaries of the segments. Fig. 3 shows an example of segmentation achieved using the described method.

C. Feature Extraction

The features extracted from the signal include the average and standard deviation of the amplitude, power spectral density estimate peaks, energy and power of the signal, energy entropy of the signal and the zero crossing rate of the EEG signals.

Power spectral density estimate peaks were looked at to have a description of the rate of oscillation of signal (distance between peaks) and a description of the shape of oscillation of the signal(relative amplitude of peaks). These features were chosen because the sleep events, leg movement and arousal events, to be detected are associated with spikes in the EEG signals being measured which correspond to changes in the strength of the signal and changes in the oscillation of the signal.

The *energy* of a discrete-time signal, $x_i(j), j = 1, ..., N$ for the i^{th} frame, where N is the length of the frame is defined as

$$E(i) = \sum_{j=1}^{N} |x_i(j)|^2$$

The *power* of the signal can be obtaned by normalizing the frame energy by dividing the value obtained from the equation above by the length of the frame, N, to remove the dependency on the frame length. The energy of a signal is expected to have high variation over signal frames where arousal events occur, that is to say that the energy envelope quickly varies between high and low energy states for signal frames containing arousal events. Due to this property of EEG signal energy during arousal events, an additional feature that can be paired with

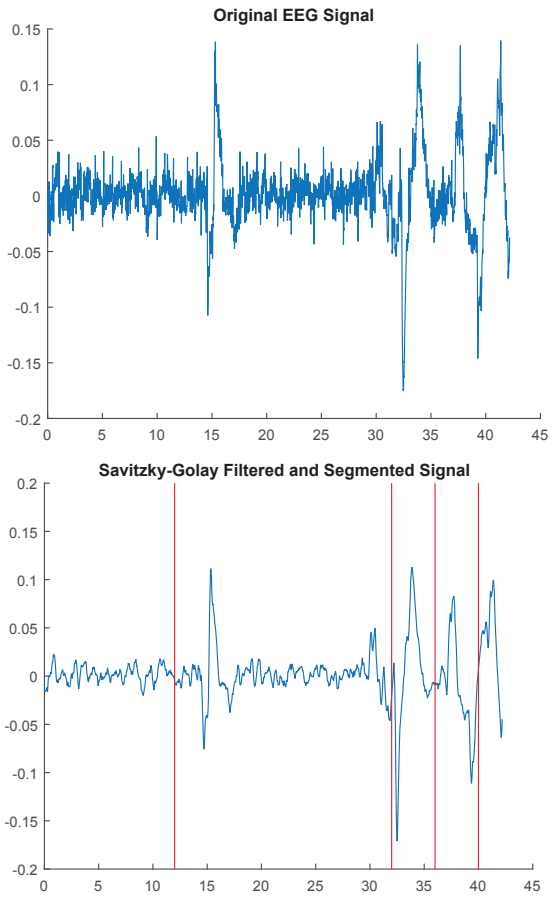

Fig. 3. **Top:** Original signal. **Bottom:** Filtered and segmented signal.

the energy of the signal to increase classification performance would be the standard deviation of the energy envelope. An alternative to this pair of features that doesn't depend on the intensity of the signal would be to use the ratio of the standard deviation to the mean of the energy of the signal, which can give a significant performance boost depending on the application [13].

The *zero-crossing rate* describes the rate of sign-changes of the signal during a specified time and can be interpreted as a measure of the noisiness of a signal, that is to say that noisier signals have higher zero crossing rates, and as a way of describing some of the spectral properties of a signal. The zero-crossing rate of a discrete-time signal, $x_i(j), j = 1, ..., N$ for the i^{th} frame, where N is the length of the frame is defined as

$$Z(i) = \frac{1}{2N} \sum_{j=1}^{N} |sgn[x_i(j)] - sgn[x_i(j-1)]|$$

where $sgn()$ is the sign function. In certain applications such as binary classification of audio signals, the standard deviation of the zero crossing rate over multiple signal windows can be used to distinguish between different types of signals, for example speech and music signals [13]. In the context of biosignal processing, [21] describes a complexity measure,

fractal dimension values based on a detrended zero-crossing function, which is used to compare irregularity of time series data in terms of the signal's complexity. The complexity of an ECG and EEG signal can be used to differentiate between intricate phenomena such as emotion, imagination and movement for the purpose of medical diagnosis. For our purposes, we used a modified crossing-rate where we subtracted the mean value of the signal frame from each data point in he frame before computing the zero crossing rate since time series data with a high complexity value can be obtained from the high rate of the zero-crossing point, that is to say that the complexity of the time-series data can be directly computed from the zero-crossing rate of the signal.

The *energy entropy* of a discrete-time signal, $x_i(j), j = 1, ..., N$ for the i^{th} frame, where N is the length of the frame is defined as

$$H(i) = -\sum_{m=1}^{K} e_m \cdot log_2(e_m)$$

where e_m, which can be considered a sequence of probabilities, is the ratio of the energy of the subframe to the energy of the window for one of K sub-frames of a fixed length. That is, for subframes e_m, for $m = 1, ..., K$, we have

$$e_m = \frac{E_{subFrame_m}}{E_{window_i}}$$

where

$$E_{window_i} = \sum_{k=1}^{K} E_{subFrame_k}$$

. The energy entropy of a signal measures abrupt changes in the energy level of a signal, where a low energy entropy indicates that there are abrupt changes in the energy envelope of the signal. This is a result of the fact that if one of the subframes, m_0, has a high energy value, $E_{subframe_{m_0}}$, relative to the other subframes, then the corresponding value for e_{m_0} will be high and reduce the entropy of the sequence e_m. This feature is useful for detecting events where there is a considerable change in the energy of the signal; for example, an audio signal of three gunshots will show that at the beginning of each gunshot the energy entropy of the signal drops noticeably [13]. In [22], the energy entropy of EEG signals was used to preprocess motor imagery EEG data to enable a more reliable classification of four types (left hand, right hand, foot and tongue movements) of motor imagery. The choice of energy entropy of EEG signals is useful because EEG signals typically have poor spatial resolution and low signal-to-noise ratio for specific physical activity that occurs simultaneously with background physical activity [22].

The *power spectral density estimate* of the EEG signals was obtained using Welch's method which returns an array of power measurements and the associated frequency vector, which we then used to obtain the main peaks of the power measurements and their locations to use as features. Welch's method splits data into overlapping segments of windowed data and finds the average of their periodograms which allows for power spectral density estimates that have less variance than other periodogram methods [23]. The Welch spectral estimate of the i^{th} discrete-time signal frame, $x_i(j), j = 1, ..., L$, where L is the length of the frame, is defined as

$$\hat{P}(f_n) = \frac{1}{K}\sum_{k=1}^{K} I_k(f_n)$$

where the K modified periodograms, I_k, are defined as

$$I_k(f_n) = \frac{L}{U}\left|A_k(n)\right|^2$$

for $k = 1, 2, ..., K$, where

$$f_n = \frac{n}{L}$$

for $n = 0, ..., \frac{L}{2}$,

$$U = \frac{1}{L}\sum_{j=0}^{L-1} W^2(j)$$

and $W(j)$ for $j = 0, ..., L-1$ are data windows used to form the sequences $X_1(j)W(j), ..., X_K(j)W(j)$ and $A_1(n), ..., A_K(n)$ are the finite Fourier transforms of these sequences [24]. [25] describes the use of the power spectral density estimate of EEG signals as a feature for effectively describing disturbed brain activity that can be used for detecting epileptic seizure events. Due to the ability of the power spectral density estimates' relative peak distances and amplitudes to describe the shape and rate of the oscillation of EEG signals, we used it as a feature for detecting arousal and leg movement events.

D. Event Detection

The current study focuses on detecting two types of events, using only the EEG signals collected by the 8 available channels. These events are:

1) Arousal from sleep,
2) Left and right leg movement.

An "arousal from sleep" event is a micro-awakening or an abrupt change of EEG from a deeper stage of NREM sleep to a lighter stage, or from REM sleep toward wakefulness, with the possibility of awakening as the final outcome. Such an event can be triggered by various causes (e.g. a sleep apnea), and may be accompanied by increased chin (EMG) activity and heart rate, as well as by an increased number of body movements. Increased arousals are associated with increased daytime sleepiness and decreased performance, similar to that seen in sleep deprivation.

A "leg movement event" is a more simple type of event, which just denotes that some leg movement occurred. It can be triggered by disorders like the *restless leg syndrome*, or it can just be the result of awakening due to some other cause. In any case, it is an indicator of disruption from normal sleep.

Classification: Our event detection problem can be reduced to a classification problem by taking each segment (window) of the signal and testing it against a classifier that decides if that segment contains an event of interest or not. In our

situation, we have a different classifier for each different type of event, thus forming a binary classification problem. The added benefit of this approach is that in each segment we can detect more than one type of events. For example, a segment can include both a leg movement and an arousal event, which is actually very common in sleep studies.

To classify the signal segments, we follow a supervised learning approach, where the system is first trained using segments with known event labels, and subsequently it is tested on segments with unknown labels. Our dataset contains 121 arousal events, 342 right leg movement and 359 left leg movement events. The supervised learning algorithms used and compared in this work were *Naive Bayes*, *Logistic Regression* and *Decision Trees*, as implemented in MATLAB. 10-fold cross validation was used to train and test the classifiers for each event type.

IV. Experimental Results

In this section, we present and discuss the experimental results of applying the methods discussed in the previous section to detect the two types of events of interest: (1) arousal events, and (2) left leg movement and right leg movement. It should be noted that the leg movement event is broken down into two event sub-types, i.e. *left leg* movement and *right leg* movement. We attempt to detect each one of those separately.

We evaluate the performance of our methods by applying three standard metrics commonly used in pattern recognition, namely *Accuracy*, *Recall* and *Precision* values, for each combination of classification algorithm and segmentation technique, as shown in Table II.

A. Detecting Arousal Events

The first case of interest in our experiments is to detect whether the person is being aroused from sleep. This is useful in cases, for example, for detecting common sleep disorders such as hypopnea, obstructive sleep apnea and restless leg syndrome where an arousal event follows events such as oxygen desaturation, an increase in breathing effort and leg movements. EEG arousals can be observed as abrupt shifts in EEG frequency lasting at least 3 seconds and preceded by at least 10 seconds of sleep.

The highest accuracy obtained for arousal event detection was accomplished by the Decision Tree (DT) classifier, for both the fixed window segmentation and the adaptive window segmentation, at 84.84% and 90.57% respectively. While the Decision Tree (DT) and Logistic Regression (LR) classifiers had an increase in performance for accuracy, recall and precision, when the adaptive segmentation was used, the Naive Bayes (NB) classifier had a drop in performance in accuracy and recall, in addition to being the worst performing classifier in those categories. However, the Naive Bayes classifier performed the best in terms of precision for both the fixed window segmentation and adaptive segmentation as well as having an increase in precision from the fixed window segmentation to the adaptive segmentation.

B. Detecting Left and Right Leg Movement Events

Another case of interest is to detect when leg movement occurs during the patient's sleep. Like the arousal event, the detection of leg movement can be related to various sleep disorder symptoms. Movement at the end of an obstructive apnea event can be seen in the chin EMG channel, the snore microphone and the leg EMG channels. Another common sleeping disorder that affects more than 80 percent of people with restless leg syndrome is periodic limb movement of sleep which is characterized by involuntary leg twitching or jerking movements during sleep that typically occur every 15 to 40 seconds, sometimes throughout the night (National Institute of Health, National Institute of Neurological Disorders and Stroke, 2010). In general the most accurate biosignal to detect leg movements would be the leg muscle EMG signal, when available. However since this study focuses on EEG signal analysis, we used the 8 EEG signal channels to detect leg movement.

The highest accuracy obtained for left leg movement event detection was achieved by the Decision Tree for both the fixed window segmentation and the adaptive window segmentation at 74.86% and 88.39% respectively. Just as with the performance statistics of the arousal event, the Decision Tree and Logistic Regression classifiers had an increase in performance in accuracy, recall and precision, when the adaptive segmentation was used, while the Naive Bayes had a drop in accuracy and recall and overall worst performance in all the performance statistics with the exception of precision. Similar performance trends were seen in the right leg movement event detection.

Overall, as expected, the adaptive, variable-length signal segmentation achieves better results compared to the fixed window.

V. Conclusion and Future Work

This work presented our effort in developing the methodology for automatically detecting events of interest, related to sleep disorders. Our preliminary experimental results show that the event detection goal can be successfully achieved, while our methods can also be applied to sleep data collected using alternative to PSG, non-invasive sensors, which is the ultimate goal of our effort. Future work will include detecting more types of events, using more data for each type of event, and experimenting with more classifiers and extracted features, to achieve the best accuracy possible.

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TABLE II
EVENT DETECTION ACCURACY RESULTS.

Arousal Event

Fixed Window Segmentation			
Classifier	Accuracy	Recall	Precision
DT	**84.84%**	**95.48%**	87.91%
LR	77.73%	84.71%	88.83%
NB	78.10%	82.99%	**90.71%**
Adaptive Segmentation			
Classifier	Accuracy	Recall	Precision
DT	**90.57%**	**98.92%**	91.43%
LR	89.91%	97.24%	92.12%
NB	65.62%	67.09%	**93.27%**

Left Leg Movement Event

Fixed Window Segmentation			
Classifier	Accuracy	Recall	Precision
DT	**74.86%**	**90.38%**	79.94%
LR	73.75%	83.85%	82.67%
NB	68.21%	67.58%	**88.91%**
Adaptive Segmentation			
Classifier	Accuracy	Recall	Precision
DT	**88.39%**	**98.03%**	89.96%
LR	86.99%	96.11%	90.09%
NB	57.97%	57.65%	**92.92%**

Right Leg Movement Event

Fixed Window Segmentation			
Classifier	Accuracy	Recall	Precision
DT	**74.86%**	**90.19%**	80.42%
LR	73.84%	86.57%	81.52%
NB	67.10%	66.82%	**88.82%**
Adaptive Segmentation			
Classifier	Accuracy	Recall	Precision
DT	**89.79%**	**98.55%**	90.94%
LR	87.44%	95.46%	91.11%
NB	57.35%	57.20%	**93.05%**

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