Limbs Movements Detection and Classification using EMG signals

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1. ABSTRACT

Periodic Limb Movements during Sleep (PLMS), are commonly reported in patients with different sleep disorders as insomnia, sleep apnea or narcolepsy, meaning that they can have a negative impact in the sleep quality. Nowadays, its detection is done by polysomnographic monitoring interpreted by a sleep medicine physician according to a specific group of rules that characterize the PLMS representing a long-time challenging task that can be expedite by the implementation of a system capable of classify the LMS between periodic or non-periodic, that can be used by both experts and non-experts.

The algorithm developed in this project detects leg movements during sleep and classify them between periodic or non-periodic. Besides, different features of interest are obtained, like the start and final times of each PLMS evet, the quantity of movements in the event and the mean movement duration. These can be used for future analysis of the processed signals as well as the development of more sophisticated systems.

2. PROBLEM AND MOTIVATION

Abnormal limb movements may occur during sleep and have a negative impact in the sleep quality. There are two sleep disorders that can be responsible for periodic limb movements during sleep (PLMS) when typically take place in the lower limbs: the periodic limb movement disorder (PLMD), which involves PLMS caused by involuntary contractions of the muscles during sleep; and restless legs syndrome (RLS), characterized by disagreeable leg sensations that provoke an urge to move legs [1].

The PLMS are characterized by dorsiflexion of the ankle, dorsiflexion of the toes and a partial flexion of the knee and sometimes the hip, lasting between 0.5 and 5 s. To determine the frequency of PLMS occurrence, the PLMS index (PLMI), calculated as the number of PLMS per hour of total sleep time, is commonly used. [2]. In children, PLMI greater than 5/h is considered abnormal and in adults a PLMI greater than 15/h. The PLMS criteria of the current American Academy of Sleep Medicine (AASM), indicates that movements may have a duration of 0.5 to 10 seconds, occur at 5 to 90 seconds intervals in series of minimum 4 LM [3], for periods of 10 minutes to several hours [4]. The World Association of Sleep Medicine (WASM) has another rule for classifying PLMS: the LM should last more than 0.5 seconds and occur at 10 to 90 seconds intervals in series of minimum 4 LM.

According to the revised ICSD, mild PLMD is defined as mild insomnia or hypersomnia with a PLMI of 5–34, moderate PLMD as moderate insomnia or hypersomnia with PLMI of 25–49, and severe PLMD as severe insomnia or hypersomnia with a PLMI of more than 50. [5]. Nowadays, the diagnosis of them is done by self-reported questionnaires and polysomnographic monitoring interpreted by a sleep medicine physician, but PLMS scoring is the classification of periodic LM along a set of LM identified according to a specific group of rules. According to Fulda, the rules themselves are fully specified and although complicated, their application requires no expert judgment and can be automatically produced by a suitable automated program, even there are groups currently working in systems for scoring and classification of PLM, but these are just partly available. This represents an opportunity to develop a system capable of detecting and classifying the limb movements of the electromyography (EMG) recordings from a polysomnography (PSG) and then also propose a statistical model to recognize the syndrome.

The system developed is an algorithm supposed to classify LM in periodic or not according to AASM 2.4 criteria. First, the signal is smoothed for a better detection of its variations in time. Then, potential LM are detected with a pre-established threshold obtained from a resting section of the signal and divided between actual -or not- LM. Afterwards, it does a scanning of the LM movements in order to see which of them meet the characteristics of a PLMS event or not, i.e. if there are 4 LM or more in a raw. When classification is completed, a set of characteristics are extracted for each event, periodic or not: number of events, quantity of movements in the event, initial time in seconds, final time in seconds, and mean movement duration. During the process, general characteristics, i.e. of the signal itself, are obtained: total PLMS events, total non-PLMS events, total PLMS, total non-PLMS, periodic limb movements index (PLMI) and hours of sleep.

Future applications in the area could focus in more precise classification systems like the implementation of artificial neural networks or fuzzy logic given the characteristics that the system is able to obtain. For this, it could be useful to acquire other different characteristics of the potentials of the signal when PLMS events are present. In addition to just go through the classification of LM as periodic or not, there could be statistical developments to find correlations between PLMS and patterns in other biological signals recordings, and other relative symptoms reported by the patients to detect different sleep syndromes easily and in a more reliable way.

3. BACKGROUND AND RELATED WORK

There are multiple factors that can be related with poor sleep and excessive daytime sleepiness as PLMD or RLS. These includes various sleep disorders, medical and psychiatric conditions, and sleep deprivation or due to medication effects. [6] Over time, sleep has been better recognized as an important element of optimal physical and mental health. But the detection of the sleep problems is often dependent on the patients reporting them. There have been different assessment tools to detect sleep disorders. Some of them are questionnaires (subjective sleep measures) used depending on the aspect of interest in the evaluation, are self-reported instruments to characterize the sleep-wake function. They require the intervention of clinician or researchers for the data interpretation and usually go with a backup diagnoses process, i.e. a PGS study Some of them are described below.

The Pittsburgh sleep quality index (PSQI) is a self-rated questionnaire which assesses sleep quality and disturbances over a l-month time interval. Nineteen individual items generate seven “component” scores: subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleeping medication, and daytime dysfunction. Each is weighted equally on a 0-3 scale. The sum of scores for these seven components yields one global score, higher scores indicate worse sleep quality [7]. The Patient-Reported Outcomes Information System (PROMIS) aims to build item pools and develop core questionnaires that measure key health-outcome domains manifested in a variety of chronic diseases as well as build an electronic Web-based resource for administering computerized adaptive tests, collecting self-report data, and providing instant reports of the health assessments [8].

Epworth Sleepiness Scale (ESS) is a simple, self-administered 8-item questionnaire which provides a measurement of the subject's general level of daytime sleepiness. The ESS assesses the likelihood of dozing in different common situations using a 4-point Likert response format (scored from 0 to 3 with higher scores indicate more severe sleepiness). Item responses are summed to obtain a total score ranging from 0 to 24, with a score greater than 10 indicating excessive daytime sleepiness. [9].

The International Restless Legs Syndrome Scale is a self-report questionnaire used to assess the RLS severity [10]. So, despite the self-reported instruments allow to characterize the sleep-awake relations, and quantify latent variables such as sleep quality, they are not useful to typify PLMS or RLS. The electrophysiologic techniques, as PSG are used to characterize these sleep disturbances, but only through its interpretation made by a expert, i.e. a sleep medicine physician.

There have been developed some expert systems that emulate the human capacity of diagnosis in the field of sleep medicine. One of them is Sleep Expert, developed by Korpinen and Frey in 1993, and is an interactive program composed of 288 separate integrated submodules and 264 text files. The program includes eight reasoning questions about symptoms setting the limits for the diagnosis subset. The user obtains a list of possible diagnoses on the screen where he/she can examine their criteria [11].

The Sleep-EVAL, developed by Ohayon et al. in 1999, was the first expert system designed specifically as a diagnostic instrument for use in clinical or epidemiological studies of sleep disorders. It is a non-monotonic, level-2 knowledge-based system endowed with a causal reasoning mode designed to provide homogeneous and standardized diagnostic evaluations. The system comprises a knowledge base, an inference engine, a neural network, a mathematical preprocessor, and a user interface [12]. Basically, the system begins with a questionnaire suitable to all subjects; based on the responses, it draws a series of diagnostic hypotheses followed by the building of a decisional tree and the formulation of new questions to be asked for completing the information it already has. This exploration continues until a final decision is made with respect to the first hypothesis. Then, the same process is followed for other hypothesis until it runs out of possibilities.

The decision is made by the inference engine and it depends on the neural network to manage the uncertainty in the responses and reject or confirm a diagnosis. When there are special instructions in the knowledge base, the inference engine calls on the mathematical preprocessor which performs some mathematical operations to allow the system to verify the collected data and detect inconsistencies.

Besides the self-report based diagnose, there is another modality available which allows the physician to enter the following polysomnographic results into the system: EEG nighttime or daytime recording; electro-oculography (EOG); electromyography; electrocardiogram; oximetry; CO2 monitoring; airflow (nasal, oral); esophageal manometry (PES); body temperature monitoring; MSLT; HLA typing; nocturnal penile tumescence (NPT); esophageal ph; snoring sound; and video monitoring. The data allows the system to produce a revised diagnosis.

In 2011, Kravoska et al., develop a research to find the best set of characteristics of polysomnographic signals for the automatic classification of sleep stages. They carry out a multidimensional analysis involving quadratic discriminant analysis and their best automatic sleep classifier achieved an 81% agreement with the hypnograms of experts [13]. This classifier was based in 14 features of polysomnographic signals carefully selected. In other research in 2018, Savareh et al., compared the performance of a support vector machine and an artificial neural network for sleep scoring using wavelet tree features and neighborhood component analysis. They achieved 89.93% and 90.30% accuracy, respectively [14].

4. APPROACH AND UNIQUENESS

4.1 Material

The data used was a set of fourteen edf (European data format) files. They consist of the storage of multichannel biological and physical signals, i.e. PSG recordings. The different measurements available for working, includes electroencephalogram, electrooculogram, surface electromyogram, electrocardiogram, respiratory inductance plethysmography, pulse oximetry and thermistor measured oral and nasal airflow. The one that is of interest for the objectives of this project, is the leg EMG, which was extracted as well as its duration, sample frequency and number of records for the signal processing.

4.2 Methods

Data processing

The signal of interest (EMG PERNA) was extracted from the edf file. A time vector was obtained using the number of records, duration of each and sampling frequency, information available in the edf file as well. The signal was full wave rectified by acquiring que absolute value of all the elements of the signal and then normalized as shown in the Figure 1.

The filtering consisted in two steps for smoothing the signal. First, an 8th-order lowpass Butterworth filter was designed with a cutoff frequency of 2,5 Hz, for data sampled at 64 Hz, in order to remove high frequency components. Then, a weighted moving maximum smoothing filter with a centered window of 64 elements was applied to generate the final processed signal as can be observed in Figure 2.

In order to detect the movement, the single threshold method was applied: the amplitude of the entire smooth signal was compared with a threshold defined by adding 0.08 to the maximum value of the signal inside an interval in which the patient is in repose. When a value was higher than the threshold, the correspondent variable of a new vector was assigned 1 and 0 in opposite cases. The value of the threshold chosen was 0.08 because, according to the main PLMS scoring criteria of the current AASM manual (version 2-4), to measure an onset of a leg movement (LM) there should be an increase of 8 uV above resting EMG [Fulda]. To detect the offset of each pulse, the time between pulses was reviewed and if it was shorter than 0.5 s, then the two pulses were considered as one now.

Data Analysis

Once the potential leg movements vector was obtained, the data was analyzed to determine if they were actually leg movements, and then to classify them between periodic or not periodic movements. If the potential movement has a duration between 0.5 and 10 seconds, then it was classified as an actual LM (accordingly AASM 2.4). The next step with the LM detected was obtaining the time between the consecutive onsets and determine if they were periodic or not. In the AASM 2.4. For a set of LM to be considered a PLMS event it is needed at least 4 LM in series, an inter-movement interval (IMI) between 5 and 90 seconds and the end of the series when the IMI is greater than 90 seconds.

4.3 Proposed solution

The solution for classification was extracting the position of the LM that meet the condition of an IMI value between 5 and 90 seconds in a vector, needed to be considered PLMS, and put them in a new array in order of appearance in the signal (1, 2, 3, 4, 8, 13, …). Some of them will be consecutive while other will not. Then, it was possible to go through the vector with a while cycle, inside which, new conditions are established: it checks if the current position is consecutive with at least next three positions (e.g. 6, 7, 8, 9, …), then the event will be considered as PLMS. If it is not consecutive or is consecutive with less than the three next positions (e. g. 6, 8, 13, …; or 7, 8, 9, 12, ...), the LM was classified as simple or non-periodic.

The next characteristics for each event (PLMS or not) are printed: number of events, quantity of movements in the event, initial time in seconds, final time in seconds, and mean movement duration. General characteristics are also displayed: total PLMS events, total non-PLMS events, total PLMS, total non-PLMS, periodic limb movements index (PLMI), and hours of sleep. At the end, the user has the option of reviewing (or not) different signals in parallel deciding the length (in seconds) of the view window: original signal, rectified signal, filtered signal, LM detection signal and classification.

5. RESULTS AND CONTRIBUTIONS

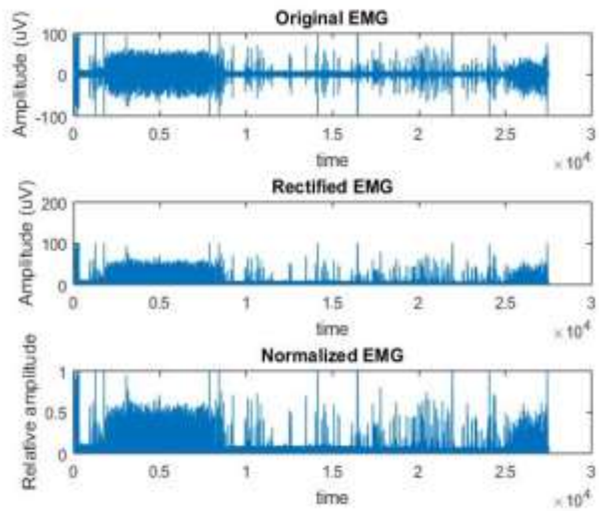

Figure 1. Original, rectified and normalized EMG signals of the patient 17853A - C.

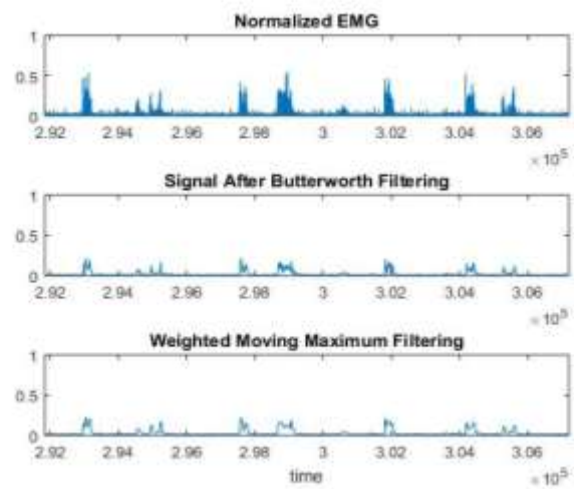

Figure 2. Normalized signal, signal after applying the Butterworth filter and signal after applying the weighted moving maximum filter within an interval of 120 seconds.

In the Figures 1 and 2, rectification and filtration, the different steps of signal processing before detection and classification can be observed within a complete sleep cycle. In the Figure 3 it is possible to observe the evolution of the signal within the different steps of the algorithm: rectifying, filtering, LM detection and movement classification. Regarding to the classification, the red line represents a PLMS event that starts before that set of samples and finishes after. The program allows the user to select the size of the view window to review the evolution of the signal within different time intervals. The Table 1 displays the number of PLMS events, the number of total PLMS, the PLMI and the hours of sleep computed by the system in the EMG signal of 6 different patients. For most of the tested signals, the classification results are consistent when running the program in various occasions.

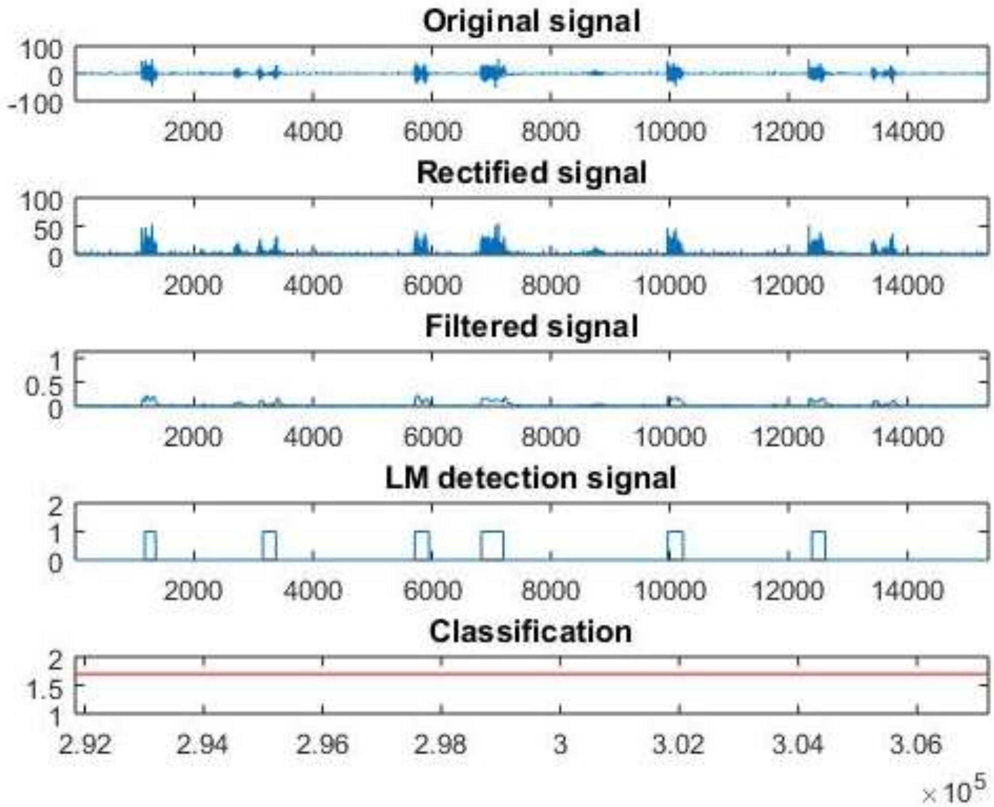

Figure 3. Comparison of the EMG signal of the sample 17853A-C within the different steps of the algorithm: rectifying, filtering, LM detection and movement classification. The length of the interval observed is of 120 seconds.

Table 1. General characteristics score obtained from the EMG of 6 different patients.

Sample	PLMS events	Total PLMS	PLMI	Hours of sleep
17853A-C	19	305	39.9	7.64
17572A	40	379	53.6	7.06
17711AP	13	85	13.8	6.151
17738A	44	367	52.8	6.94
17798A	16	137	19.8	6.91
18046AT	2	11	1.30	8.26

6. DISCUSSIONS AND CONCLUSIONS

The principal objectives of the project were the detection and classification of LMS in periodic and non-periodic. Comparing the different steps of the signal processing (Figure 3), it is possible to observe that the pulses that represent the LM detection are in the same position where movement is seen in the original signal. This represents a good rectifying and filtering process. The full wave rectifying (Figure 1) gave as a result a better signal for following processing, i.e., it has enough information for the subsequent filtering. The Butterworth filter had good effects for filtering the noise of the signal, even if it keeps with the EMG characteristic noise. Because the weighted moving maximum smoothing filter allows to obtain the main trend of the signal, which later results in good movement detection in most of the cases.

Regarding to the classification, it is apparently correct because the pulses showed in the image meet the conditions to be PLMS, and the red line is activated. The system still skips some actual movements, but this characteristic could be improved with a better method for the threshold adjustment. Nevertheless, as the implementation of the rules for its detection is a challenging and long task, the system represents a good alternative for the signal analysis because it extracts different variables of interests, as the start and final times of each PLMS evet, the quantity of movements in the event and the mean movement duration, and it is possible to consult another variables if needed or storage them in a file more accessible for the clinicians. The data collected can be used for future research in sleep disorders related with PLMS, and for further feature extraction to train automated classification systems, which would be able of obtaining better results than the algorithm implemented in the project. It could be useful as well to acquire other different characteristics of the potentials of the signal when PLMS events are present. In addition, there could be statistical developments to find correlations between PLMS and patterns in other biological signals recordings, and other relative symptoms reported by the patients to detect different sleep syndromes like PLMD, easily and in a reliable way for more effective diagnosis.

7. REFERENCES

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