Analysis and Patterns Recognition of Biomedical Signals Related to Sleep Stages

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***Abstract*—Sleep is a vital, often neglected, component of every person's overall health and well-being. Sleep is important because it enables the body to repair and be fit and ready for another day. Getting adequate rest may also help prevent excess weight gain, heart disease, and increased illness duration. One of the most common problems on today's society are the sleeping disorders and for that reason over the last decade a lot of studies have been made to help people with this kind of problem and more recently with the help of the increment on technology, Automatic Sleep Stage Classification (ASSC) systems have been developed to assist specialists in the sleep stage scoring process and therefore in the diagnosis of sleep disorders. This paper presents a framework that continues a project which combines an ASSC system and a binaural beat generator but more focused on the recognition of patterns during the sleeping process. For these we evaluated three different classifiers using data retrieved from a public database from different test subjects. Our proposed framework may lead to a system capable of recognizing the different sleep stages with good accuracy and be part of a fully automated system to improve sleep quality without needing medical interaction.**

***Index Terms*—Sleep Stages, ASSC, Database, Classifiers**

I. INTRODUCTION

Sleeping Is one of the most important activities in human development. It helps to maintain physical and mental health. In recent times this topic has been explored in more detail and has been noticed that the fewer people sleep, the most chances they have to develop health problems such as fatigue and even hearth problems.

One of the most common problems in recent years is sleep disorder, which has several repercussions on people's health as this can lead to heart problems, reduced concentration, memory problems, etc. Based on this, several studies have emerged that are looking to improve the quality of people's sleep. One of the main studies that have emerged in recent years and have gained momentum is *Automatic Sleep Stage Classification* (ASSC). The purpose of these techniques is to identify the different sleep patterns of each person and using that information experts can implement measures to improve the rest process of patients in a better way.

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Many ASSC systems can be found in the literature and have shown accuracies above 90% accuracy. In a previous phase of this project, it was developed an ASSC system that can reproduce binaural beats to potentially help people fall asleep faster, maintain their sleep, and wake up at the best possible time [1]. In this paper, we propose a framework that can recognize sleep patterns using an ASSC system to determine the sleep stages in real-time.

II. BACKGROUND

A. Automatic Sleep Stage Classification Systems (ASSCS)

Polysomnography (PSG) is the primary tool used for quantitatively assessing sleep and involves concurrent acquisition of multiple physiological signals comprising the electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), and electrocardiogram (ECG). Standardized rules for sleep staging using PSG were first laid out by Rechtschaffen and Kales (R&K) in 1968. In 2007, the American Academy of Sleep Medicine (AASM) combined the best available evidence with the consensus of experts in sleep medicine and sleep science to modify the R&K rules, resulting in a higher inter-rater reliability (IRR) of sleep staging than with the RK system. Under the modified rules, the number of sleep stages was simplified to 5: Wake (W), Stage 1 through Stage 3 (N1, N2, and N3), and REM [2]. Stages 3 and 4 from the R&K rules were collapsed to N3 in the revised scoring criteria, and movement time (MT) was no longer considered as a separate stage [3].

Numerous automatic sleep stage classification schemes have been proposed and demonstrated, but time consuming and resource intensive human expert review remains the main method by which sleep staging is performed in most clinical and sleep research labs worldwide. Automated systems typically incorporate particular carefully engineered features extracted from PSG data into a classification algorithm. Features that have been extracted from PSG data include spectral power, band power, wavelet coefficients,amongst others. Classification algorithms include support vector machine, Gaussian mixture models, artificial neural networks, learning vector quantization, amongst others. Some methods apply sophisticated artifact correction prior to feature extraction. The accuracy associated with existing automated methods varies from between 75% and 95%. In most instances, the classifier was validated using samples containing less than 100 hr of data with some work being supported by as little as 10 hr of validation data [4].

B. Sleep Stages

There are four sleep stages; one for rapid eye movement (REM) sleep and three that form non-REM (NREM) sleep. These stages are determined based on an analysis of brain activity during sleep, which shows distinct patterns that characterize each stage.

NREM Sleep Patterns

NREM sleep is composed of three different stages. The higher the stage of NREM sleep, the harder it is to wake a person up from their slumber.

Stage 1 / N1

Stage 1 is essentially the "dozing off" stage, and it normally lasts just one to five minutes. During N1 sleep, the body hasn't fully relaxed, though the body and brain activities start to slow with periods of brief movements (twitches). There are light changes in brain activity associated with falling asleep in this stage. It's easy to wake someone up during this sleep stage, but if a person isn't disturbed, they can move quickly into stage 2. As the night unfolds, an uninterrupted sleeper may not spend much more time in stage 1 as they move through further sleep cycles [5].

Stage 2 / N2

During stage 2, the body enters a more subdued state including a drop in temperature, relaxed muscles, and slowed breathing and heart rate. At the same time, brain waves show a new pattern and eye movement stops. On the whole, brain activity slows, but there are short bursts of activity that actually help resist being woken up by external stimulation.Stage 2 sleep can last for 10-25 minutes during the first sleep cycle, and each N2 stage can become longer during the night. Collectively, a person typically spends about half their sleep time in N2 sleep [5].

Stage 3 / N3

Stage 3 sleep is also known as deep sleep, and it is harder to wake someone up if they are in this phase. Muscle tone, pulse, and breathing rate decrease in N3 sleep as the body relaxes even further.The brain activity during this period has an identifiable pattern of what are known as delta waves. For this reason, stage 3 may also be called delta sleep or short-wave sleep (SWS) [5].

Experts believe that this stage is critical to restorative sleep, allowing for bodily recovery and growth. It may also bolster the immune system and other key bodily processes. Even though brain activity is reduced, there is evidence that deep sleep contributes to insightful thinking, creativity, and memory. We spend the most time in deep sleep during the first half of the night. During the early sleep cycles, N3 stages commonly last for 20-40 minutes. As you continue sleeping, these stages get shorter, and more time gets spent in REM sleep instead [5].

REM Sleep Patterns

During REM sleep, brain activity picks up, nearing levels seen when you're awake. At the same time, the body experiences atonia, which is a temporary paralysis of the muscles, with two exceptions: the eyes and the muscles that control breathing. Even though the eyes are closed, they can be seen moving quickly, which is how this stage gets its name [5].

REM sleep is believed to be essential to cognitive functions like memory, learning, and creativity. REM sleep is known for the most vivid dreams, which is explained by the significant uptick in brain activity. Dreams can occur in any sleep stage, but they are less common and intense in the NREM periods.

Under normal circumstances, you don't enter a REM sleep stage until you've been asleep for about 90 minutes. As the night goes on, REM stages get longer, especially in the second half of the night. While the first REM stage may last only a few minutes, later stages can last for around an hour. In total, REM stages make up around 25% of sleep in adults [5].

III. Proposed Framework

The proposed framework is described in Figure 1 which is an ASSC system that acquires, processes, and classifies the sleep patterns in real time using three different types of structures.The system should be as non invasive as possible so that it can be used in different environments.

Data Acquisition

In this stage, the system uses a special device capable of obtaining different types of signals (mainly EEG), then the data is sent to the computing system to be processed.

Processing Data

This stage consists of processing the data that was obtained in the previous stage and applying different techniques like filters and centering the data, all this depends on the signal that is processed and all his requirements.

Feature Extraction

In order to use the processed data is necessary to create a feature vector. The dimension of this vector depends on the number of features extracted. Features are used to obtain different information about the signal and can be on time/frequency domain.

Training

This is a task that has to be done before the system can run. The classifiers have to be trained using properly labeled signals, so the classifiers can learn how to recognize the different patterns.

Classification

In this stage, the features vectors are applied to the classifiers to determine the current sleep stage. This stage needs to be fast and accurate in order to get a good classification in real-time.

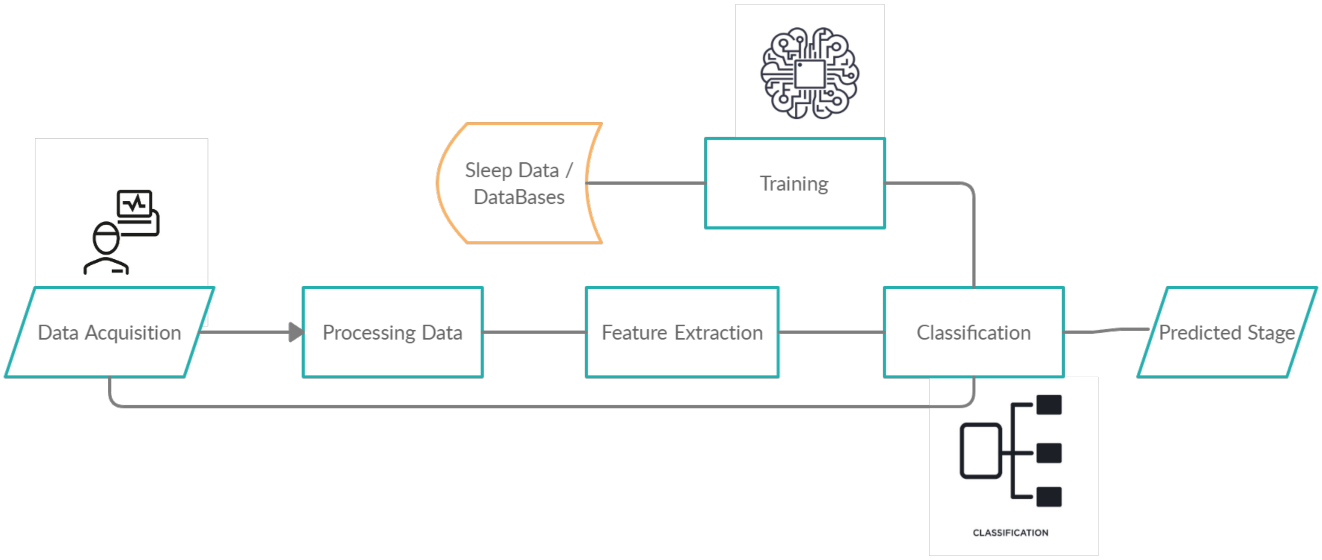

Fig. 1. Proposed Framework.

IV. Experiments and Results

Following the previously established process, two methods were used to validate the proposed framework. These two methods consist of conducting the tests using data obtained from a public database with annotations made by experts and the other method consists of conducting the tests using data obtained in real time.

A. Experiments Using Sleep Recordings from a Database

Several tests were performed using different sets of polysomnography recordings obtained from a public database called PhysioNet [6], which contains different sets of recordings of healthy men and women between the ages of 26 to 34 years. All these measurements were carried out at night with an approximate duration of between 5 hours and 30 min to 9 hours and 50 min, indicating when the lights were turned off to give a starting point and based on that to be able to classify according to the standards international Each of the different tests carried out belongs to one of the hypnograms present in the database where the separation of epochs is made every 30 seconds. The channels used for these tests were the Fpz-Cz and Pz-Oz channels, horizontal EOG and submental EMG.To get this data a Toolbox developed by [7] was used to downlad and convert the data to a MATLAB fotmat so it can be processed on the ASSC

For the classification three of the best known classifiers were evaluated which are: Support vector machine (SVM), Neural networks (NN) and k - nearest neighbor (KNN). For the support vector machine a linear kernel was used. The NN selected was a two layer model with 10 neurons in the hidden layer and for the KNN we worked with the 10 closest neighbors. Five time, power and statistical domain features were chosen to represent the sleep stage signals: Mean Absolute Value (MAV), number of Zero Crossings (ZC), kurtosis, slow wave activity (SWA) and the Maximum Minimum Distance (MMD). Those features were applied to the signals to get different information in the different domains, for example the slow wave activity is used to identify Delta frequencies along the sleep process.

	Avg. Accuracy (%)		
Test Subject	NN	SVM	KNN
1	89.2 %	82.6 %	86.9 %
2	95.4 %	83.8 %	86.2 %
3	94.1 %	85.2 %	85.7 %
4	91.9 %	83.7 %	87.1 %
5	92.1 %	84.2 %	86.6 %

TABLE I
Average Correct Classification Accuracies. 10-Fold Cross-Validation Results.

The features were extracted out of every sleep epoch starting from the lights out time registered in the recordings, as mentioned in [7]. A 10-fold cross validation was performed for both classifiers, for every recording. Five classes were considered: sleep stages 1; 2; 3, REM sleep and wake stage. The average classification results are shown in Table I

Another way to represent the accuracy of the classifiers is by using a confusion matrix which shows the true classes and the predicted ones in the X and Y axis and with that information the user can visualize in a detailed way every class with his respective success rate on Figure 2 it shows a confusion matrix for one test subject using a NN.

B. Experiments Using Real Time Recordings

A Cyton Board from OpenBCI [8] was used for the data acquisition stage. The Cyton Board can be used to sample brainwaves (EEG), muscular activity (EMG), ocular activity

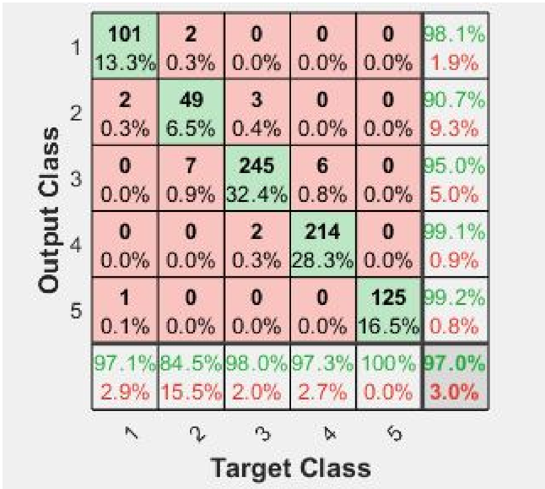

Fig. 2. Confusion Matrix using an NN.

(EOG) and even heart rate (ECG). For these tests, only EEG signals collected with an Electro-Cap were used.

For the processing data stage, two second-order IIR Butterworth digital filters were applied to the EEG signals. These types of filters are commonly used since they can easily be realized and have great frequency responses at low orders. The first filter is a band-pass with cutoff frequencies at 1 and 50 Hz. The second one was a notch filter at 60 Hz to further eliminate possible AC noise in the signals. Commonly on projects related to EEG signals, developers implement different bandpass filters to decompose the signals into the different brain waves (alpha, delta, theta, beta, and gamma). As saw on [1] using two Butterworth filters can provide good accuracy. Therefore in this project, we dint implement any extra filter to decompose the obtained signals.

Once's the signal is processed the feature extraction stage captures the signal and divides it into different epochs of 30 seconds in order to process and extract the different features (MAV, ZC, SWA, Kurtosis, MMD) of every time interval. For the classification stage is important to mention that in this work, we did not get sleep stage annotations from experts for the EEG signals acquired with the Cyton Board and the Electro-cap. Base on that, the classifiers were trained using the EEG data available on the Physionet database. This allowed us to run different tests to the proposed framework using our hardware to obtain the signals to be classified. For the training stage, we use the three classifiers described in section IV-A, Extracting also the same features described in the feature extraction stage.

Once the classifiers are trained and ready to use, the EEG signals from the test subject can be applied to the whole system in order to get the label of the sleep stage that the test subject is currently on at the time every epoch happens. This process runs continuously until the test subject wakes up the next morning.

V. Discussion and Conclusions

The proposed framework one of the first steps towards a system capable of recognize sleeping patterns, the different stages of the framework were implemented and verified using sleep data from public databases and data acquired in real time.

The first sets of experiment we were available to reach the level of accuracy of those reported on [1], those experiments were implemented using simple features and medium training level. Therefore, implementing more sophisticated features and a better training method we could expect better results on the classification. One important thing to have in mind is that the goal of this project is not to compare the different classifiers that were evaluated, the goal was to explore the different classification techniques between a reasonable computational requirement.

Having reach a good accuracy using basic configurations, we train the classifiers in a more robust way, the NN were trained using the Bayesian regularization which is a network training function that updates the weight and bias values according to Levenberg-Marquardt optimization. It minimizes a combination of squared errors and weights, and then determines the correct combination to produce a network that generalizes well [9]. This training method usually better in complex patterns but takes longer to train.

For the second set of experiments an important thing to mention is that we can't guarantee the accuracy of this experiments. However, seeing at the results showed on Figure 2 and Table I we expect the same amount of accuracy on these tests showing that the proposed framework can obtain the EEG signals and process them in order to get a real time classification. For future phases of these project we expect to integrate this classifiers into a binaural beat generator in order to develop a bigger and better version of the one that where presented on [1] and improve the sleeping process of different people without requiring medical attendance.

VI. Acknowledgment and Statement

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