Sleep Monitoring Classification Strategy for an Unobtrusive EEG System

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Abstract—**the advances in the wearable devices and Artificial Intelligence domains highlight the need for ICT systems that aim in the improvement of human's quality of life. In this paper we present the sleeping tracking component of an activity and sleeping tracking system. We present the sleep quality assessment based on EEG processing and support vector machines with sequential minimal optimization classifiers (SVM-SMO). The performance of the system demonstrated by respective experiments (accuracy: 83% and kappa coeff: 72%) exhibits significant prospects for the assessment of sleep quality and the further validation through an evaluation study.**

Keywords: sleep stages; EEG; SVM;

I. Introduction

The evolution observed nowadays in the domain of pervasive health and wellbeing assisted from the maturation of Internet of Things (IoT) technologies has led to the hyper growth of the market regarding wearable devices and applications related to health and fitness. According to [1], the respective market is expected to increase rapidly from US$750 million in 2012 to US$5.8 billion in 2018.

Nevertheless significant work has been published so far, regarding systems employing data mining techniques that are tailored on the detection of specific pathological anomalies (heart diseases, epilepsy, etc.) [2]. On the other hand the multi-modal acquisition of data and context from wearable devices gains also interest and attraction. These data along with respective algorithms are expected to help researchers to extract meaningful patterns that will help them to monitor and detect human's daily routines that jeopardize his health and deteriorates quality of life in short or long term.

The significance of sleep quality is strongly connected with quality of life since it directly affects mental health [3]. At the same time, literature highlights the coexistence of sleep disorders with chronic diseases as well. Therefore, tools for the sleep quality assessment and interventions for its improvement could significantly contribute towards a qualitative life. Pilot studies have manifested the strong relation among sleep quality and physical exercise [4].

These systems however need to address many contradictory challenges. First of all, in order to achieve a high degree of adoption by the end users and hence commercial success, they need to operate unobtrusively and seamlessly without distracting the users. At the same time, they need to collect data and produce knowledge that could have medical meaning for doctors and users.

In that context this paper presents the design and development of a sleep and activity tracking platform that intends to deliver unobtrusiveness and a more fine grained sleep and activity analysis. This paper extends the primary work presented in [5] by focusing on the sleep stage identification component integration as well as system's architecture design and implementation along with some preliminary results.

Section II presents a brief description of the background, regarding sleep staging and the most popular approaches followed for similar systems. Section III decomposes the system in its components while in Section IV we present the intelligence core of the proposed system that is responsible for the sleep stage identification and sleep quality assessment. The paper concludes in Section V and summarizes the progress made so far along with the future steps to follow.

II. Background & Related work

The sleeping session is a dynamic process that consist of sleep stages and is described by the transition from one to another along with the total time spent on each stage. Namely, the sleep stages are discriminated in Wakefulness (W), stage 1 (N1), stage 2 (N2) (these two stages are characterized as light sleep), stage 3 (N3) (characterized as deep sleep) and Random Eye Movement (REM).

According to literature, the golden standard for the accurate sleep stage classification is polysomnography (PSG) along with the R&K rules scoring system as restructured in 2007 by the American Academy of Sleep Medicine (AASM) [6]. The guidelines for this particular methodology require the use of at least 6 EEG channels, 2 electromyography (EMG) leads attached to the chin and 2 electrocculography (EOG) leads that track eye movements. Obviously, such a setup is cumbersome for the person that needs to track his sleep as it can be feasibly applied only in lab environments, with experts' assistance and not on as a daily routine.

The devices that flood the market recently, such as Fitbit Flex [7], utilize an alternate, yet less obtrusive method, the actigraphy. Actigraphy is applied through a wearable wrist band which integrates accelerometer, capable of identifying body movements [8]. While these devices can produce results, related to the detection of sleep/wake, close to PSG, no further details

about the sleep cycle can be extracted so. Therefore, the adoption of such techniques in medical practice have been poor and only supplementary to the rest of the methods.

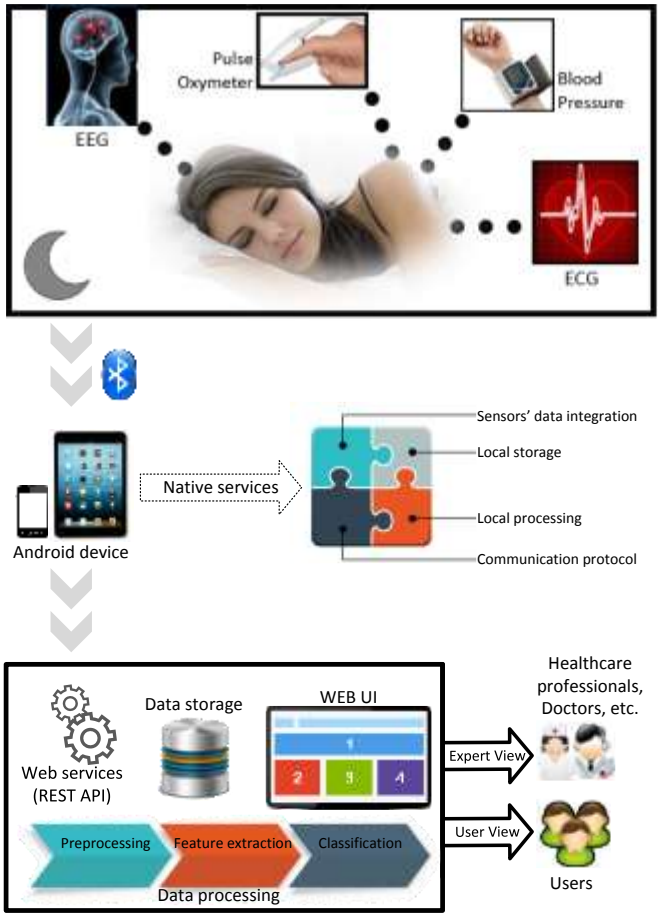

Figure 1. Sleep tracking component

Authors in [9] present a unobtrusive approach by utilizing only a smartphone's sensors (microphone and inertial measurement unit) for the detection of body movements, snoring, heartbeat and respiration while authors in [10] use a smartphone for detecting sleep patterns by studying smartphone's usage patterns (e.g., the time and length of smartphone usage) and ambient observations (e.g., prolonged silence and darkness).

EEG processing for sleep stage identification takes advantage of the recent progress in machine learning, so as to employ robust and accurate sleep stage classifiers. Authors in [11] present a feature extraction methodology and a relevance vector machine (RVM) for automatic sleep staging classification. Although they achieve a total accuracy of 76.7% they fail to detect sufficiently N1 stage (23.2%). Artificial neural networks are proposed in [12] for sleep scoring and they also achieve a significant accuracy of 81.55%. In [13] two popular classifiers are tested on how they perform on a specific feature set for online automatic sleep staging. Namely Random Forest (RF) and Support Vector Machine (SVM) were compared and the RF outperformed for the specific configuration.

III. SYSTEM DESCRIPTION

Regardless the new approaches presented in the recent literature for unobtrusive sleep monitoring, the most prominent tool to provide all the necessary information regarding the brain activity during sleep remains the single channel EEG. The ecosystem of the presented system is based on three main pillars: the wearable devices, the smartphone and the backend system. The sleep tracking component of the system architecture is presented in Figure 1.

A. *Wearable Devices*

Wearable devices are the cornerstone of all related systems for health monitoring and ambient assisted living (AAL) systems, as they constitute the raw data source. In our use case we decided to use components of the self (COTS) that employ widely adopted and popular wireless standards, such as Bluetooth or Wi-Fi, that incorporate built-in flexible and interoperable communication interfaces while at the same time the same time the devices address the needs for comfort and unobtrusiveness.

In that context, the EEG source is based on the MyndPlay BrainBandXL which is a commercial EEG recording product, based on the Neurosky platform, with two dry sensors and an ear clip as a reference point. The Surface Mount Device (SMD) board is attached on a headband made of a soft and comfortable fabric. The wireless connectivity offered by the MyndPlay platform is based on Bluetooth.

However, the modalities supported by the proposed platform are not restricted to the EEG. The activity recording depending on the user profile and his comfort zone may varies from a simple step counter to fitness and medical chest straps for ECG recording. At the moment the presented system supports 2 activity recording modes. The most unobtrusive and simple is the step counter provided by the smartphone, while for a more sophisticated heart activity recording the Zephyr BioHarness is employed. Zephyr BioHarness encapsulates 2 conductive ECG sensor pads and 1 internal breathing sensor. The wireless connectivity remains the Bluetooth.

Finally, the proposed system also integrates the A&D Medical – UA-767BT automatic blood pressure monitor along with the NONIN 4100 pulse oximeter as complementary metrics for the completeness of user's health profile. Both devices provide Bluetooth connectivity.

B. *Smartphone Functionalities*

The smartphone platform could be any Android device with Bluetooth and Wi-Fi connectivity. The smartphone provides a twofold contribution to the system.

The first and primary role of the smartphone is derived by its capability for providing interconnection between the wearable devices and the backend system, thus playing the role of a gateway. Communication drivers have also been implemented

and deployed at the application level for the interaction with each wearable device. The required connectivity is implemented as individual android services that run in the background. As long as a paired wearable device of the user is detected, in the vicinity of the smartphone's wireless interfaces, a connection is established and the smartphone receives either data streams from EEG and ECG sensors or single values from the pulse oximeter and blood pressure monitor devices. All received values are temporary stored in the smartphones internal storage until they are transmitted to the backend system for further processing and storage.

The second functionality that the smartphone provides is derived by the native services that any Android device implements. For example, step counter values are also gathered and provide some primary indication of the person's activity while the GPS sensor can enhance the activity record with speed and distance covered during running.

C. Backend System

The backend part of the proposed system is responsible for acquiring and storing data that have been collected by the wearable devices during each user's sessions and transmitted via the Android services deployed within the smartphone. Apart from simple data gathering, the backend system also incorporates some data processing components for high level information creation and storage. Overall, the backend system consists of four main components as described below.

- Web services provider for data gathering. This component is mainly responsible for gathering, handling and further processing of transmitted data from the smartphone services. Since continuous recording of EEG and ECG signals can easily derive huge amount of raw data a special treatment has been applied as a custom communication protocol between the backend system and the smartphone's services towards minimization of data volumes that have to be transmitted. Such a technique results in major advantages in processing and storage resources in backend as well as in mobile pillar of the proposed system. Finally the component is responsible for feeding the visualization component (Web UI) through proper web interfaces.

- Data processing. The software modules responsible of the processing of the biosignals and the physiological data along with the respective classifiers are integrated in the backend system. An extensive description of the processing conducted on the EEG for the sleep stage classification is presented on Chapter IV.

- Data storage. Raw data together with extracted high level information from data processing component are stored in backend's database which is deployed under a typical MySQL server. On top of the database engine an ORM framework, with a tiny processing and memory footprint, is responsible for abstracting the actual database records, thus enabling large scale employment.

- Web application (Web UI) for system's stakeholders. The backend system is finally responsible for providing useful information (such as advices, tips, etc.) to all involved stakeholders. The presentation view of such information is responsive to the stakeholder type. For example typical user's view includes his activity history in a timeline basis and some advices/tips that are specified by his corresponding doctors or health care team. At the same time doctors and health care professional have full access to either visualize a user's raw data or become aware of features extracted from raw data (i.e. sleep stages from EEG, HR-artifacts from ECG, etc.). Doctors' view has the ability to intelligently adapt the relevant information from simple diagrams to cohesive dashboards in order to enable the doctor to get the most with the less possible effort and interaction.

IV. SLEEP QUALITY ASSESSMENT

In this paper we focus on how the proposed system handles the sleep related biosignals and specifically the EEG which is a non-stationary, nonlinear and noisy signal. EEG is an error-prone signal since it coexists with stronger biosignals that interfere and introduce noise as artifacts. These artifacts originate mainly from ECG, EMG and eye blinks. Further noise is introduced by the power line inference and the body movements. The methodology followed for the identification of sleep stages consists of three sequential steps: signal preprocessing (artificacts/noise elimination), feature extraction (frequency & time domain analysis) and final the classification.

To eliminate this noise as much as possible without eliminating valuable sleep frequencies we apply a 2nd order butterworth filter with low and high cutoff frequencies set at 0.3 and 40Hz respectively. Since the EEG is a non-stationary signal, it is processed in epochs of 30 seconds where stationarity is assumed.

Subsequently, the filtered signal feeds the feature extraction algorithms so as to extract the set of parameters that describe the brain activity during the sleep cycle. For that purpose we follow a frequency and time domain analysis and we calculate the most dominant features that are documented in the literature for sleep stage classification.

The sleep stages described in Section II are manifested in the EEG as frequency components. Therefore, we perform a respective spectral analysis in order to obtain the EEG power density spectrum based on Welch's method [14].

Further features obtained from time domain analysis include the estimation of mean, max and min values as long as standard deviation and variance. The Zero Crossing Points value is another promising feature that manifests the presence of spindles that occur mainly in Stage 2. The set of the dominant features for the sleep stage identification is completed with the estimation of Hjorth Mobility & Complexity, Kurtosis, Skewness and Interquartile range along with the auto regressive filter coefficients occurred from the 6th order auto regression analysis of the signal [15].

The classification scheme implemented in our system is based on Support Vector Machines with the Sequential Minimal Optimization (SMO). Our prototype classification model has been built on data obtained from Physionet [16] and particularly the MIT-BIH polysomnography sleep database [17]. This database consists of 18 records obtained from 16 subjects with the method of polysomnography. From this database we utilized the EEG records which where sampled with a frequency of 250Hz. All the records are segmented in epochs of 30s duration and annotated based on the initial sleep scoring scheme (4 non-REM stages) by medical experts.

The method followed for the performance assessment of our classifier was based on the 10-fold Cross Validation. This method splits the dataset in 10 independent and disjoint test sets with almost equal class distribution. The classifier is trained with the remaining data left from the i-th test set and tested on the i-th test set. The experiments are repeated 10 times for each i-th test/train dataset for i=1:10. The performance metrics of the classifier occur from the average of the 10 repetitions.

Our analysis was based mainly on two statistical measures, the total accuracy and Cohen's kappa coefficient. As accuracy is defined as the ratio of the correct predictions across all classes divided by the total number of instances. For more coherent interpretation of the classification results we employ the kappa coefficient as an indicator of the relative improvement of the classifier over the random predictor.

The first experiment was conducted with all the instances of the database as input to the classifier. Our initial aim was to identify the three main sleep stages, namely wakefulness, light sleep (stages 1, 2 and REM) and deep sleep (stages 3, 4). This resulted in unbalanced dataset with 10181 instances. The results are depicted in Table I.

TABLE I. UNBALANCED DATASET - SVM CONFUSION MATRIX

Classified as:	W	(S1,S2,REM)	(S3,S4)	Total
W	**2147**	966	7	3120
(S1,S2, REM)	487	**5775**	135	6397
(S3,S4)	7	233	**424**	664
Total	2641	6974	566	10181
	TP rate = 69%	**TP rate = 90%**	**TP rate = 63%**	**Acc=8346/10181 =82% Kappa = 63%**

While the model occurred from this dataset performed with an accuracy of 82% it doesn't identify every class with the same accuracy. Respective True Positive (TP) rates present that our model is biased towards the light sleep stage (TP rate 90%). This is also indicated from the kappa coefficient value which reaches the 63%. In order to improve the predictability of our model we fed the classifier with a balanced dataset. The new dataset consists of the 664 instances of the deep sleep class and 664 instances randomly chosen from wake and light sleep classes respectively. The performance our classifier achieved is presented on Table II.

TABLE II. BALANCED DATASET – SVM CONFUSION MATRIX

Classified as:	W	(S1,S2,REM)	(S3,S4)	Total
W	**541**	118	5	664
(S1,S2, REM)	80	**515**	69	664
(S3,S4)	11	49	**604**	664
Total	632	682	678	**1992**
	TP rate = 82%	**TP rate = 78%**	**TP rate = 91%**	**Acc = 83.33% Kappa = 72%**

The strategy followed in the second experiment achieved a slight increase in the accuracy (83.33%) but significant improvement in the prediction capabilities. The kappa coefficient value reached 72% while the TP rates where more equally balanced among the three classes. The TP rate of deep sleep outperformed with a TP rate of 91% which was expected as the deep sleep stages are manifested more clearly in the EEG.

V. CONCLUSIONS

In this paper we presented the main architectural and implementation approaches followed for the development of an activity and sleep tracking system. The main focus of the particular paper was the sleep tracking component of the presented system. The EEG processing and classification strategy which we followed, tested on data provided by open databases (MIT – BIH polysomnography), achieved significant performance on the prediction of sleep stages therefore we are confident that it will be validated through a respective evaluation study.

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