Data Acquisition System for Sleep Stage Detection: Signal Processing

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Abstract

The project here described consists in the development of a computational tool capable of automated Rapid eye movement (REM) sleep stage detection making use of data acquired from standard sleep analysis sources. For this purpose an acquisition system for biological signals was developed [1]. It acquires electromyogram (EMG), electroencephalogram (EEG) and electro-oculogram (EOG) channels, processing the data in near real-time according to REM sleep characteristics in frequency and time domain, exporting the result of each evaluated 30 second epoch in a REM stage probability indicator. After the designed digital signal processing (DSP) achieved satisfactory results in preliminary trials using a training data set acquired with a commercial setup, signals acquired with the developed device were tested. Flaws were detected revealing the need of improvements not only in the data acquisition (DAQ) design but also in the preprocessing methodologies. Once fixed, trials were done and confronted with an expert evaluation achieving good results. The applied DSP module was further tested for better results, with the development of an automatic definition of criteria thresholds and application of Independent Component Analysis (ICA) for artefact removal.

1. INTRODUCTION

The goal of this work is the elaboration of a "path" according to which it is possible to detect characteristic sleep features and consequently detect REM sleep.

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1.1. Background

One of the most common phrases concerning sleep is "A normal human being spends about a third of his live sleeping". It is also a commonplace to think that sleep is a sort of loss of time. Contradicting this idea, studies have shown that sleep is indeed one of the strongest forces guiding human behaviour [2]. A better understanding of sleep could explain its functions, justifying what we are doing during that one third of our lives, as well as identifying pathologies which can be studied through sleep stages. At the onset of sleep stage investigation, methods such as variations of waking threshold, motility and breathing were used. Nowadays they can actually give some information but in the beginning of the XX century could only promote divergent opinions since no sleep stages were known, therefore it was impossible for a researcher to know which events he should seek. Sleep stage definition came with Loomis et al. [3] and the discovery of REMs by Aserinsky and Kleitman [4]. Later on, justifying the cyclic evidences of sleep condition already noticed in breathing, cardiac cycle frequency and other parameters, Dement and Kleitman [5] introduced the cyclic patterns of sleep stages based on their large normative study. The four non-REM (NREM) stages and REM stage formed the basis of subsequent polygraphic sleep studies, as depicted in Fig.1.

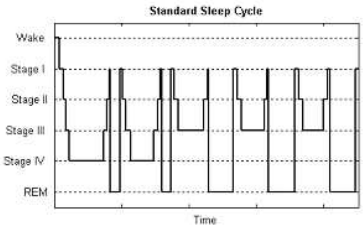

Figure 1: Standard sleep cycle. [6]

These different sleep stages were firstly "created" due to different encephalic waves throughout sleep.

Brain activity started being categorized by frequency in distinct groups: Δ, θ, α and β, represented in table 1. These bands aid in the sleep identification since the predominance of one of them, or an event associated to a defined band would suggest a specific stage.

Table 1: EEG frequency bands

Δ	0 - 4 Hz
θ	4 - 8 Hz
α	8 - 14 Hz
β	14 - 30 Hz

By using an EEG tool as a feature extractor, associated with other records - e.g. EMG and EOG - it became possible to generically study sleep. Naturally, due to a large set of data to be analyzed, different approaches and subjectivity associated to each researcher, results were discrepantly classified by different polysomnographic expert analysts. The need of a common platform for exchanging data and results led to the establishment of a committee, in 1968, led by Rechtschaffen and Kales (R&K) [7]. The main goals of the committee were to standardize recording and scoring techniques in order to increase the comparability of results between laboratories (e.g. definition of a sleep time scale - epoch[1]). A manual was created providing the minimum requirements for meaningful comparison of polygraphic sleep studies on adult humans. In search for both the within and between researcher groups agreement in sleep stage identification and to foster the development of computer algorithms for automatic analyses of sleep, in 1991 the necessity for additional definitions was recognized, reformulating the R&K rules to cover information that was identified from 1968 to 1991: 1) different sleep epoch discretization could lead to an improvement in sleep stage classification, therefore sleep epochs with length from 5 seconds to the standard 30 seconds were evaluated. 2) Since sleep analysis does not focus only on healthy subjects, R&K rules were reformulated to cover pathological conditions [8]. Results deviation associated with previous mentioned barriers and the fact that sleep identification is an extremely time consuming task, have motivated an increased development of methodologies capable of detecting unequivocally, if possible, different sleep stages in the shortest time possible. This assumes significant proportions because certain sleep stages carry information beyond its sleep stage. For instance, REM sleep is one of the stages carrying more relevant information - e.g.: the number of rapid eye movements recorded can inform about a possible schizophrenic situation or depressive patients [9, 10, 11, 12]; studies of rapid eye movement occurrence in blind subjects [13]; narcolepsy detection; this stage is associated with memory formation [14] as well as dreaming. All this lead to the need of a correct REM stage identification so that future work can accurately take place. For this purpose an acquisition system for biological signals was developed, manipulating the acquired data and exporting through an interactive interface the output of REM sleep stage characterization in a real time scenario. In this sense the project here presented, is of great value in order to reduce time and cost of the analysis and increase the sensitivity of subsequent statistical analysis.

[1]according to R&K 30s were the time unit to be analysed, identified as an epoch with a defined sleep stage

1.2. Sleep Parameters

For a correct and guided determination of sleep stages it is essencial to adequately recognize its associated phisiological manifestations. Since EEG, EMG and EOG were the chosen signals for the study, it is important to be aware of the sleep manifestations associated to each source. For the present work, REM sleep stage identification, one must be capable to detect “strange” characteristics, such as, encephalic activity resembling wakefulness (paradoxical sleep), absence of muscular activity only disturbed by sporadic contractions, and the characteristic that gives the name do this sleep stage, rapid eye movements. The proposed DSP module uses the mentioned input signals, detecting patterns and events according to the R&K rules as presented in Fig.2, differentiating in real time REM sleep stage.

Sleep Stage	EEG	EOG	EMG
Awake – eyes closed	α waves	Self control	Tonic activity relatively high; voluntary movement
Awake – eyes open	Low voltage; mixed frequencies	Self control	Tonic activity relatively high; voluntary movement
NREM1	Relatively low voltage; mixed frequencies; θ waves may be highly expressed	Slow eye movements	Tonic activity weaker than awake stage
NREM2	Low voltage; mixed frequencies; presence of sleep spindles and K-complexes	Slow eye movements on sleep onset	Weak tonic activity
NREM3	20% ≤ Δ waves ≤ 50% with variable amplitude	No activity	Tonic activity
NREM4	Δ waves > 50% with variable amplitude	No activity	Tonic activity
REM	**Low voltage; mixed frequencies; presence of θ and slow α waves; absence of Δ waves**	**Rapid eye movements**	**Atonia; muscular twitchs**

Figure 2: Characteristics of each sleep stage. [15]

2. DSP

2.1. EEG Algorithm

In what concerns the EEG, the goal of the work was to identify pattern detection schemes for REM sleep staging. Bearing this in mind, and Fig.2, a well designed algorithm could be conceived, Fig.3.

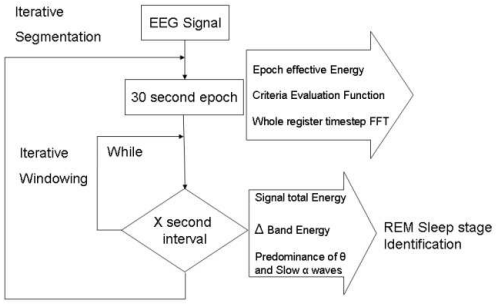

Figure 3: Suggested EEG Algorithm.

This approach segments the acquired EEG data vector in intervals of 30 seconds, Fig.4, analyzing each one of them in the frequency domain for the detection of REM sleep stage EEG charateristics.

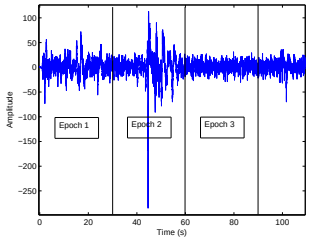

Figure 4: Example of an EEG signal segmentation.

In order to achieve a better resolution, each epoch is analyzed according to a defined fraction, 5 seconds was the applied window in the present work. A FFT tool is applied to each window in order to assess the desired characteristics. Fig.5 is an example of such process.

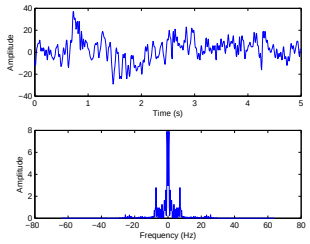

Figure 5: Example of signal analysis. The upper picture represents a 5 second EEG signal, while the lower picture represents the corresponding FFT transform.

The vizualized window is analyzed according to well defined features for REM sleep stage detection:

- Absense of Δ band activity
- Low α wave activity or predominance of θ and slow α waves
- Low amplitude signal

Once the total epoch has been analyzed, for each criterion, if $\frac{2}{3}$ of the epoch time span verifies the REM sleep stage condition, then that feature attributes a $\frac{1}{3}$ probability that the subject is in REM stage sleep. The $\frac{1}{3}$ value is atributed since there are 3 features with equidistributed weights for the EEG analysis.

As well as a REM episode detector, the algorithm exports an energy vector concerning each epoch and a whole register timestep FFT for frequency periodicity analysis.

2.2. EMG Algorithm

The EMG data acquisition system records data from the potential differences of electrodes on the chin, reflecting the muscle tone of a subject. Knowing that atonia is a characteristic REM feature, this algorithm tries to detect this occurrence. Besides considering atonia, one must also bear in mind that possible sporadic muscular contractions may occur in the middle of a REM stage without disturbing or causing any stage transition. Therefore periods of muscular atonia as well as periods with higher energy but with fast muscular contractions are detected as REM epochs. Since no specific frequency band is attributed to muscular contractions, and no frequency analysis has proven to be relevant for the muscular DSP, only time domain analysis is performed. A schematic of the designed algorithm is presented in Fig.6.

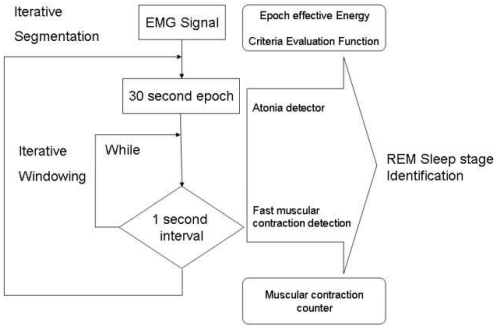

Figure 6: Suggested EMG Algorithm.

Signal processing begins with the segmentation step. This step is similar to the EEG segmentation

being timed in epochs and its energy determined. If the root mean square (RMS) of the epoch is above a defined threshold it is possible that the evaluated interval is a NREM stage epoch (Fig.7 left plot), if not, one considers it to be a REM epoch (Fig.7 right plot).

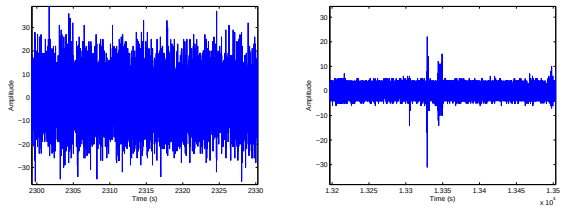

Figure 7: Left plot - Thirty second NREM epoch EMG register. Right plot - Thirty second REM epoch EMG register

For the detection of fast muscular contractions one can not analyze the signal in a epoch time, instead windowing is applied in order to evaluate each second of the epoch (see Fig.8).

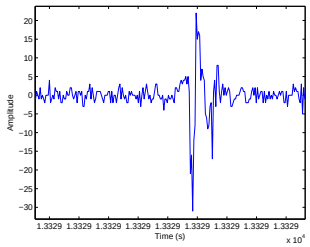

Figure 8: One second EMG data with fast muscular contraction.

This windowed signal is then split into half and both the resulting 0.5 second signals are evaluated in order to calculate its maximum variation ($EMG_{max} - EMG_{min}$). For a REM identification the maximum variation of one half second must be below a defined threshold while the other half must be above it. Since continuous fast muscular contractions may in fact be a slow twitch or even muscular tonus, the algorithm considers three muscular contractions in a row to be identified as a slow contraction and therefore discards the possibility of identifying the epoch as a REM period.

EMG analysis will consider an epoch to be REM if atonia is verified or, in cases where the RMS is higher, if this increase of energy is due to the presence of fast muscular twitches. Besides the output vectors common to the EEG analysis (REM epochs identification; Epoch effective energy; ratio of epoch's absolute maximum and effective value), counters for fast and slow muscular contractions were defined.

2.3. EOG Algorithm

The EOG signal by measuring potential differences between the front and back of the ocular globe (see Fig.9) allows a correct monitoring of the eyes.

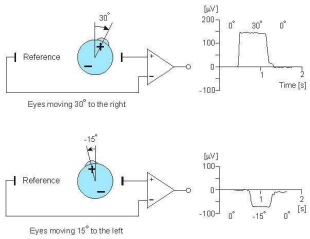

Figure 9: EOG signal generated by horizontal movement of the eyes. [16]

For this project, the detection of synchronous and fast eye movements is essential. REMs are detected as saccadic waves[2] with phase-reversed synchrony in the left and right EOG channels. In this analysis since the feature to detect is a phasic eye movement event, one must not focus on frequency but only on the time domain. A schematic for the automatic detection of REM methodology is represented in Fig.10.

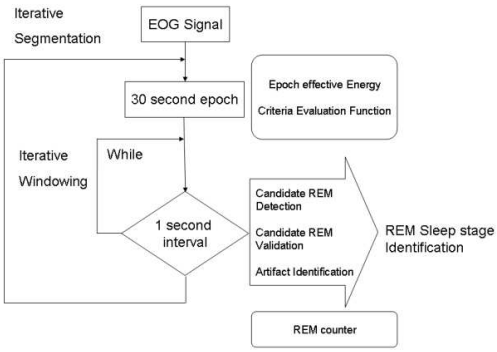

Figure 10: Suggested EOG Algorithm.

The designed algorithm starts signal analysis by detecting REM candidates. This is achieved by the Negative Instantaneous Product (NIP) of the two EOG data vectors, eq.1.

$$NIP(n) = -LOC_{filt}(n) \cdot ROC_{filt}(n) \qquad (1)$$

According to this method if ROC and LOC signals are completely out of phase a positive NIP value will occur. Instead, if eye movements are not synchronous or some other artefact is present resulting into in-phase signals, a negative value will be detected in the NIP.

[2] high amplitude signals of 1 to 3 Hz frequency

In Fig.11 two different situations are presented, a phase-reversed synchronous eye movement at 13037 s and artefacts or erratic movement at 13035 s.

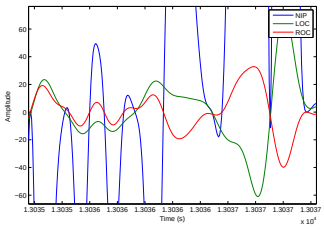

Figure 11: EOG data example. At 13037 seconds LOC and ROC registers are completely out of phase - Synchronous movement. At 13035 seconds data signals are in phase - Artefact or non-synchronous eye movement.

At this stage the data is segmented into 30 seconds epoch fragments as it is done in the EEG and EMG algorithm, for the purpose of a correct stage labelling. Afterwards, each epoch is analyzed with one second windows. The consequent one second interval is then evaluated for possible REM events. The maximum NIP value (a possible REM) is focused, $NIP(x)$, and its vicinity evaluated 0.2 seconds after and before, $NIP(x + 0.2s)$ and $NIP(x - 0.2s)$ respectively (see Fig.12). If the difference in amplitude of the ROC and LOC registers of these points is bigger than the defined threshold for saccadic amplitude variations (REM steep slopes), a REM event is considered to be present.

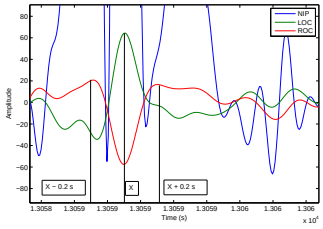

Figure 12: EOG data example. Instant of NIP maximum is focused and its vicinity evaluated 0.2 seconds before and after for REM detection

This algorithm outputs the REM stage detector, an energy vector and a REM counter.

3. Training data set

3.1. Training data

The methodologies in section 2 were tested and their results assessed for a training data set acquired by a different acquisition system. This data consisted of 6 subjects. Once analyzed, the results were contested with an expert evaluation, leading to the following conclusions. One of the subjects is here represented.

3.1.1. EEG. 1) REM sleep stage detector (Fig.13 middle plot) showed well defined REM intervals. 2) Epoch energy evaluation (Fig.13 lower plot) confirmed a low energy variability indicating a possible correct criteria definition. It was also possible to verify that the signal did not have sudden changes in energy which could be associated to artefacts. 3) The FFT analysis throughout the whole register (Fig.14) confirmed the existence of sleep cycles and its associated frequency bands.

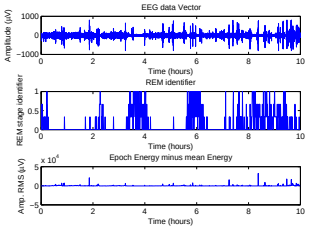

Figure 13: Subject 1 EEG analysis. Upper plot - EEG data vector; Amplitude μV. Middle plot - REM identifier. Lower plot - Epoch energy minus mean energy

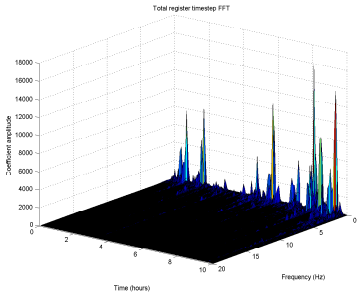

Figure 14: Total register timestep FFT.

3.1.2. EMG. 1) Demonstrated clear periods of muscular atonia (Fig.15 middle plot), value 1 intercalated with sporadic muscular contractions (Fig.15 middle plot) with value 2. After having assessed the correct functioning of the algorithm, value 1 was established for both situations, since both define REM sleep. 2) Epoch effective energy confirmed the absence of possible artefacts and the low signal variability inter-subjects.

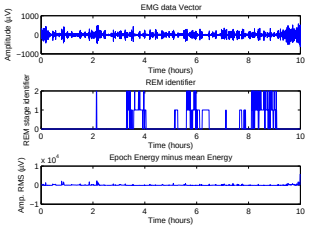

Figure 15: Subject 1 EMG analysis. Upper plot - EMG data vector; Amplitude μV. Middle plot - REM identifier. Lower plot - Epoch energy minus mean energy

3.1.3. EOG. 1) REM detection sensitivity was evaluated as illustrated in Fig.16, with the number of REMs being quantified for each epoch. After having assessed the correct functioning of the algorithm, value 1 was established for any REM identification. 2) Energy values once again assessed the inexistence of possible artefacts and the low inter-subjects signal variability.

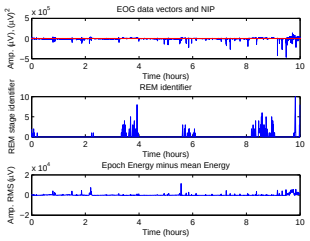

Figure 16: Subject 1 EOG analysis. Upper plot - EOG data vector; Amplitude μV. Middle plot - REM identifier. Lower plot - Epoch energy minus mean energy

3.1.4. Global Evaluation. Associating the 3 different analysis a clearer picture is achieved, Fig.17 upper plot.

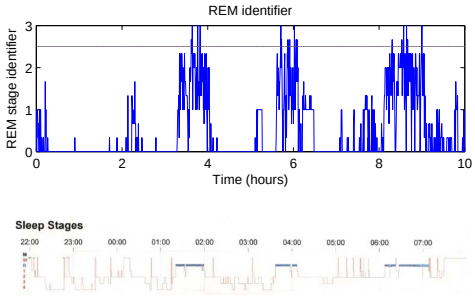

Figure 17: Upper plot - Algorithm evaluation of the presented subject. Lower plot - Expert evaluation of the presented subject

Confronting the algorithm evaluation with the expert analysis (Fig.17 lower plot), a perfect match is confirmed, with the algorithm correctly identifying the REM periods with REM stage identifier value above 2.5. Similar analysis were accomplished for the 5 remaining subjects, in which some of the REM sleep stage detections did not confirm all the criteria. This is comprehensible if one bears in mind that some data could not be considered part of the training set since the values were corrupted (e.g. saturation); the training data set registers were acquired in a sleep laboratory, being feasible that some of the subjects could suffer from sleep pathologies with their particular sleep register patterns; or even a misdefinition of criteria, due to the non adaptation of the thresholds motivated by the verified small inter-subject energy variability.

Summarizing, by strictly considering a detected REM period when REM stage identification is above 2.5, the designed setup detected 9 positive detections with 6 false negative events. This statistic reveals a 60% REM detection percentage. Although if one evaluates the REM detections bearing in mind acquisition problems and possible criteria threshold misdefinition, and therefore analyzes each epoch value comparing with the other epoch results of the same subject, a total of 14 positive detections, 2 false positives and 1 false negative were verified. In this sense the training data set revealed a very satisfactory 82% of REM detection. This global satisfactory agreement between the tested DSP methodology and the expert evaluation motivated the following trial of the designed setup.

4. Designed DAQ

4.1. First evaluation

A first trial revealed some aspects one should take into account. Using the real-time algorithm lead to unconclusive results since the signals did not have sufficient quality for the algorithm to automatically detect REM sleep stage, as confirmed in Fig.18.

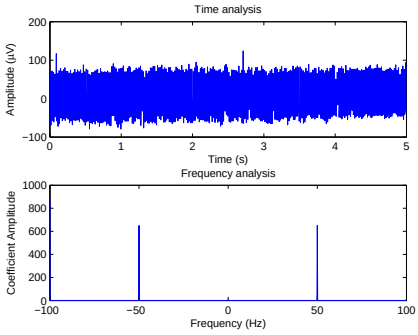

Figure 18: Designed DAQ signals preliminary analysis. Upper plot - 5 second signal. Lower plot - Frequency analysis of the acquired signal.

It was crucial to filter the signals to allow a correct detection. Since the analysis was no longer real-time, different filters were applied according to the processing needs of each signal. The specifications were: **EEG** - Low pass filter with cutoff at 45Hz ; **EMG** - Notch filter for 50Hz ; **EOG** - Band pass filter for 1-5Hz. Once the signals were correctly preprocessed, it was possible to apply the algorithm for REM sleep stage detection only by making subtle changes in criteria threshold values. These adjustments were performed since the signals were acquired by the designed DAQ instead of the previously analysed training data set signals acquired by a commercial acquisition system. This conducted to the following results.

4.1.1. Global Evaluation. The association of the three different REM stage detectors lead to three distinct possible REM stage periods, as it is represented in Fig.19.

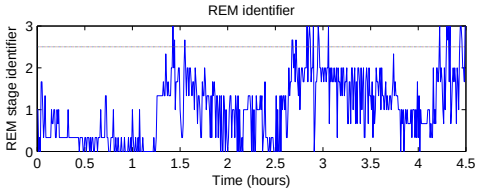

Figure 19: Algorithm evaluation of the presented trial

For this case no confrontation of the algorithm evaluation with an expert analysis was performed since modifications to the acquisition system were necessary to allow a real time evaluation in further studies. This first trial ended up being useful to detect system flaws. The identified insufficient signal quality, Fig.20 left column, motivated several modifications to the acquisition system towards signal quality improvement to allow the desired real time detection of REM sleep stage.

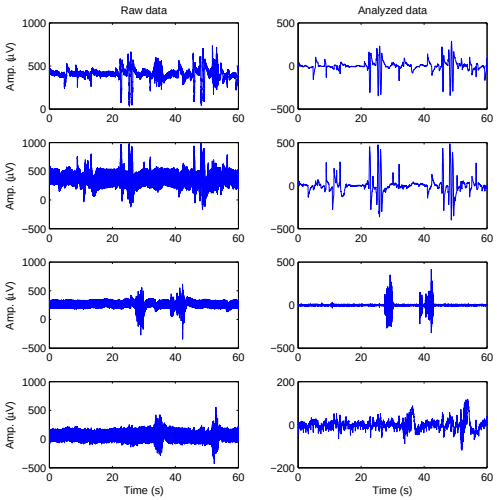

Figure 20: Raw signal vs. Desired signal quality. Left plots - Raw signal. Right plots - Desired signals.

4.1.2. First evaluation conclusions.

Blinding : Protection of the DAQ system to Electromagnetic Interference (EMI).

Cable : Instead of regular cables, coaxial cables were used reducing noise levels.

DSP : Development of parallel processes to avoid signal loss: Acquisition ; Preprocessing ; Display.

Concerning the parallel processes, modifications to the preprocessing setup took place so that signal quality changed from Fig.21 middle into Fig.21 lower plot[3].

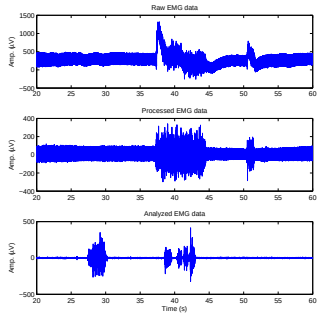

Figure 21: EMG analysis. Upper plot - EMG raw data. Middle plot - EMG processed data. Lower plot - EMG new processed data

These modifications were not applied instantly, they were being implemented and the signal quality evaluated. Four trials using regular cables were performed, followed by four trials with coaxial cables, but still with non-optimized preprocessing steps, ultimately six evaluations took place using the coaxial cables and the later preprocessing step. The advantages brought with the preprocessing step modifications focused in noise reduction and acquisition of fairly pure signals, contrarily to some tested preprocessing steps that resulted in impure data. Hence one should focus in the acquisitions with the coaxial cables and the final preprocessing step implemented. From the 6 tryouts, only 4 were correctly acquired since the remaining 2 had the following acquisition complications: 1) dettachment of the electrodes, 2) low battery of the acquisition system, which incapacitated a good acquisition and consequently a correct identification of the REM sleep stage.

In order to validate the automatic detection an expert evaluation is essencial. As a result the acquired data was converted into European Data Format (EDF) to be read in commercial softwares[4] . This format consists of a header record followed by data records. Within the header record subject and acquisition information is specified, followed by signal data records.

From the 4 correct acquisitions, only 2 were confronted with an expert evaluation. One of these evaluated registers is here presented. For each trial different criteria thresholds were applied to correctly detect REM intervals. The need to modify these values, associated with the previously mentioned misdefinition of criteria thresholds in the training data, motivated the creation of a protocol for automatic threshold definition based on signals analysis.

[3]Even though different intervals are here represented, differences in signal quality are obvious

[4]*Nicolet*^{TM}, *DOMINO Somnomedics*^{TM}, *Somnologica*^{TM}, etc

4.2. Trial 1

4.2.1. Global Evaluation. The association of the three different REM identifications is represented in Fig.22 upper plot.

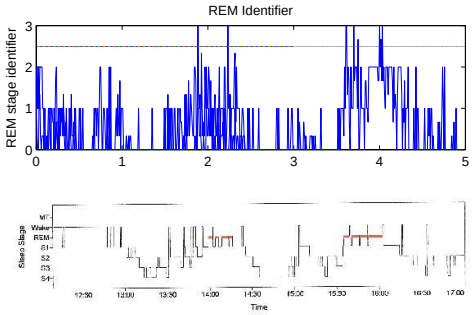

Figure 22: Upper plot - Algorithm evaluation of the first trial. Lower plot - Expert evaluation of the first trial

Even though it is not here represented, the confrontation of each separate analysis with the expert analysis verified that, similarly to the training data set, EEG and EOG detected false positives in awake situations. The EMG analysis abnormally detected false positive in awake condition assumably due to a less strict criteria definition. Associating the three vectors ended up identifying the correct REM periods. For the second trial the results were similar, detecting uniquivocally the identified REM.

4.2.2. Trial conclusions. The mentioned evaluations revealed a satisfactory 100% REM detection. Although the algorithm achieved maximum correlation with the expert evaluation, each detected interval was extremely short reflecting a high specificity, inadequate to the goal of this project. As such, it was essential to automatically define criteria thresholds for an adequate detection. For this purpose an algorithm was defined, acquiring 2 minutes of signal, and with the aid of a protocol respected by the test subject, it defines the threshold values for each criterium (e.g. Δ energy in the EEG, atonia energy levels in EMG, amplitude variation considered in a REM event, etc.) according to the evaluation of different indicators and ratios. The accomplished trials served as the starting point for a database capable of establishing these thresholds. For this task the analysis of the total register is evaluated, as well as the first 12 minutes of the register, in which the subject is expected to be awake. By analyzing sleep onset one expects the results to be similar to those acquired with the protocol to be further applied in subsequent evaluations. Besides this, another modification should be implemented in the signal processing. Interference of ocular (and sometimes even muscular) signals in the EEG was verified, motivating the evaluation of different techniques to remove such artefacts. The aplication of an ICA tool is here presented.

4.3. ICA

This methodology is based on the assumption that if different signals are from different physical processes then those signals are statistically independent. Therefore, using mathematical tools it is possible to "search" for the source signals (pure EEG, EMG and EOG) inside the mixed acquired signals. With this approach one expects to extract artefacts common to every signal, such as movement artefacts, as well as separating the different signals so that no ocular or muscular artefacts are registered in the EEG signal. Some tests with this tool lead to the following results and interpretations:

Fig.23: The ICA tool, due to its iterative procedure in search of independent components can multiply the signals for -1 instead of multiplying the unmixing matrix. This leads to inverted signals as we can verify in Fig.23 lower right plot, in which one of the EOG signals have been multiplied by -1, resulting in in-phase ocular movements. It can also swap signal positions, complicating the analysis, verified in both ICA outputs (lower left and right plots). Another problem that arises with the application of ICA tools is data normalization, disallowing the application of possible threshold values for energy and/or signal voltage.

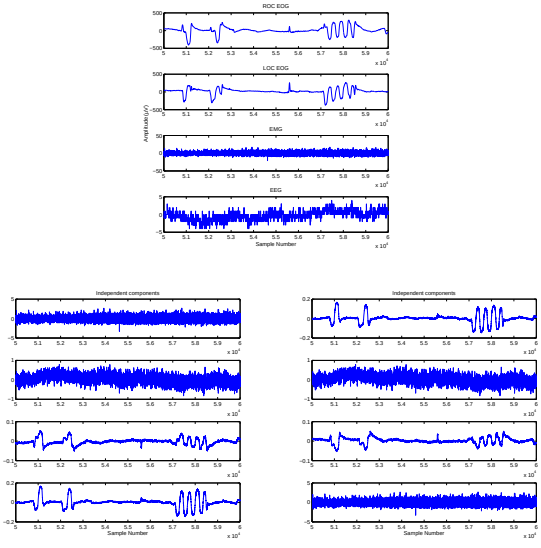

Figure 23: Upper plot - Raw signal 25 seconds sample. Lower left plot - ICA result. Lower right plot - ICA result (2)

Fig.24: If an artefact is detected with an extremely high amplitude (ROC EOG artefact of -6000μV), it will propagate to the other signals by the application of the ICA toolbox.

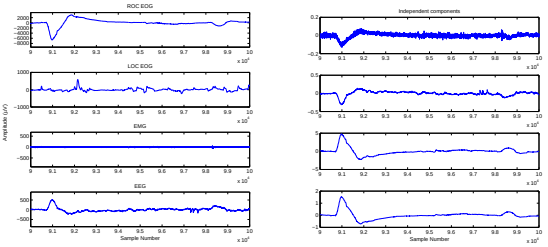

Figure 24: Left plot - Raw signal 25 seconds sample. Right plot - ICA result

Fig.25: The application of the ICA toolbox did not remove efficiently the EOG artefact in the EEG register.

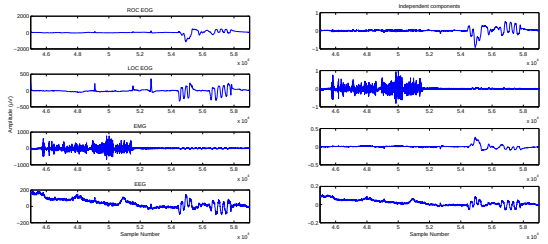

Figure 25: Left plot - Raw signal 25 seconds sample. Right plot - ICA result

Through these evaluations it became clear that ICA can not be applied to an entire data vector, expecting it to correctly separate signals and remove the ocular and muscular artifacts from the EEG register. This unsatisfactory results were assumed to be associated to the non stationarity of the used signals, due to its long time-span. Therefore, by applying ICA methodology to subsequent short intervals, followed by the gathering of such signals, one assumes that this problem is reduced. Although the previously mentioned complications associated to normalization, inversion and signal order switch are still present.

Hence a methodology was designed to unfold these complications. In such method ICA is applied to small intervals of 100 points along the analyzed signal, afterwards the resultant ICA output vectors, normalized, possibly inverted and/or swapped in position, are correlated to the original vectors. In this way the signals will assume its original values and it is possible to verify if they have been inverted - correlation will be negative - or even swapped with other signal - if correlation is maximum with a different vector in the ICA output.

Since EEG is the signal more susceptible to artefact interference, due to its low amplitude, this method was applied in order to remove artefacts from such signal, therefore combinations of 2 signals were tested: EEG and ROC EOG; EEG and LOC EOG; EEG and EMG. The results of such method were first tested in a small interval with the following results, Fig.26:

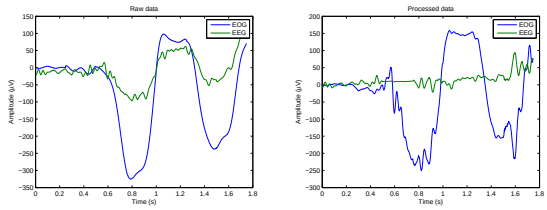

Figure 26: Left plot - Raw signal 1.8 second sample. Right plot - ICA result

This method was extended to larger intervals, as depicted in Fig.27

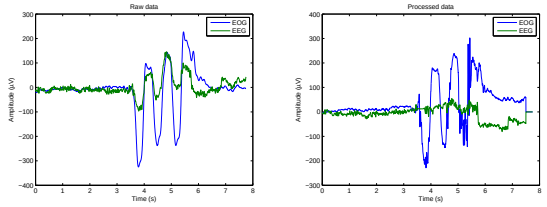

Figure 27: Left plot - Raw signal 8 second sample. Right plot - ICA result

From Fig.26 and Fig.27 it is verified that 1) ICA methodology is capable to extract ocular artefacts in the EEG data 2) EOG data should only be used in the ICA processing as input since its processing adulterates the data with EEG components.

5. Conclusions

This thesis focused on the development of the DSP tool for real time REM sleep stage identification. The designed algorithm by detecting characteristic patterns of EEG (absence of Δ waves; low amplitude signal; low α wave expression), EMG (muscular atonia with possible fast muscular twitches) and EOG (REM events) differentiated REM sleep from other sleep stages.

Initially, the designed methodology was applied to a training set of 6 subject acquired by a different DAQ device. The results revealed a 60% agreement between the automatic detection and the expert evaluation, and 82% agreement if one bear in mind some considerations: the existence of corrupted data; inapropriate data

due to possible pathological situations and possible misdefinition of criteria thresholds. In this later perspective, the REM stage detection is evaluated by comparing the result of the evaluated epoch with the result of the remaining epochs of the studied subject, independently of the 2.5 REM sleep stage threshold. This satisfactory aggreament lead to a trial with the designed DAQ system. The results from such trial were not confirmed with an expert evaluation, still the registers were used to detect flaws of the designed DAQ. Motivated by the recognized flaws and poor signal quality, modifications of the system took place: blinding of the DAQ; use of coaxial cables instead of normal cables; definition of parallel processes for acquisition, preprocessing and data display so that data was not lost. Besides these modifications, improvement of the preprocessing step was performed allowing further trials to take place with no complications. This later trials data had to be converted to a specific file extension, EDF, so that they could be evaluated by an expert, contesting the automatic identification made by the DSP setup. It revealed 100% detection of REM intervals, but the detected intervals were of extremely short time span, which is not in accordance with the goal of this project. Instead, it is desired that the DSP setup be sensitive rather than specific since there will always exist a medical monitorization of the REM sleep stage detection. This lead to the development of a protocol to automatically define criteria thresholds. Besides this modification, in order to improve signal quality, ICA was tested to remove EOG and EMG artefacts in the EEG register, as well as separate signals from common artefacts such as movement artefacts. The results of ICA have proven to be useful when applied to short intervals, so that signal stationarity is conserved. Notwithstanding some problems were identified throughout the project development, the designed algorithm fulfilled the goal of identifying REM sleep for completely acquired data vectors, and also the possibility of its implementation in a real-time setup, since it proved to be capable of processing each epoch's signal while the data is acquired and visualized. This implementation will allow future studies of REM dreaming. Even though the methodology fulfilled the aim of the project, some discussion points are here described for further consideration and investigation.

- Since the final goal of this work was to detect near real time REM sleep stage, the designed algorithm was conceived bearing in mind non pathological conditions. Although, one must be aware that sleep rules are continuously being updated and therefore it is necessary to implement its conditions in the setup in order to consider every newly discovered relevant information. For instance, it is becoming common to consider abnormal sleep stage by EEG signal similar to REM stage, the occurrence of REM events on the EOG and tonic activity intercalated with muscular contractions in the EMG.

- For the present work the epoch was defined as a 30s interval. Bearing in mind that sleep is a continuous phenomenon, it should be engaged without time discretization. Since this is not possible, the chosen epoch length is clearly a compromise between accuracy and laboriousness. One should test different epoch definitions or even overlapping epoch segments for better results. An implication of long epochs is the increased frequency resolution for the EEG analysis, while the temporal resolution is decreased. By using overlapping segmentation it could be possible to know how the transitions occur, hence promoting an easier identification of sleep stages. Another problem of sleep analysis discretization is that although they may include various electrophysiologically different states, they will only identify one of the stages. This dubious definition of epoch could be controlled with probabilistic evaluations for sleep transitions. For this purpose, one could attribute a certain probability to each transition according to the present stage and the known typical sleep cycle, Fig.1.

- Increased frequency resolution could be achieved by a different signal processing. Instead of the FFT tool a Chirp-Z transform [17] could be used. With this tool, specific time segments can be evaluated in a controlled frequency band achieving higher resolution. Focusing on the low frequency components, known to be higher expressed, promotes an increased frequency resolution.

- Other signals could be used: oximetry, ECG, limb movement, body temperature. For the present study they were not implemented since their values could not be as easily controlled as the EMG, EOG and EEG. Artefacts commonly occur in limb movement registers due to natural body movement during sleep; ECG, body temperature and oximetry are not as biologically stable as EMG, EOG and EEG, therefore the threshold definition would have to assume a more dynamic behaviour.

- More tests must be carried out to allow a liable definition of criteria values. With only two registers the threshold definition assume rough and abrupt transitions, as more tests are carried out the intervals will become more specific and therefore the criteria more adapted to each situation.

- Even though ICA revealed good results, it must be further tested to evaluate whether it can bring satisfactory results in the time span available for real time identification, and evaluated using different sample intervals so that the stationarity problem is resolved with the best solution possible. It should also be tested to remove the strong signal of ECG frequently acquired.

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