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Analyzing normalized beta wave power in EEG signals: a comparative study between C4-A1 and EMG1-EMG2 channels for RBD sleep disorder detection

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ABSTRACT

Sleep disorders are medical conditions affecting the sleep patterns of individuals or living beings, with some being severe enough to disrupt normal physical, mental, and emotional functioning. This research article discusses the analysis of the attributes and waveforms of electroencephalogram (EEG) signals in humans. The major objective is to present the findings through signal spectrum analysis, highlighting changes through various sleep stages. The objective of this research is to assess the potential effectiveness of EEG patterns in diagnosing sleep disorders, particularly those associated with rapid eye movement behavior disorder. These conditions frequently lead to detectable alterations in the electrical and chemical processes within the brain, which can be analyzed by examining brain signals and images. This research paper utilizes the short time-frequency analysis of power spectrum density (STFAPSD) method on EEG signals to diagnose various types of sleep disorders. Calculated values are normalized and the average power of the spectral signal spectra, relating to EEG wave components (delta: 1-4 Hz; theta: 4-8 Hz; alpha: 8-13 Hz; beta 13--25~30 Hz). These indices are used as diagnoses to discriminate among different types of sleep disturbances. The results comparison performs accurate power spectral density (PSD) estimations for several sleep disorders, which makes this technique highly efficient to analyze a large database in a short time. Importantly, we achieve significantly results when analyzing the normalized beta power of both C4-A1 and EMG1-EMG2 channels during the rapid eye movement (REM) stage in the EEG signal. This observation demonstrates a strong difference in PSD values (beta normalized) between normals and REM sleep behavior disorders (RBDs).

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1. INTRODUCTION

Rapid eye movement (REM) sleep is a critical stage of the sleep cycle, characterized by intense dreaming and cognitive functioning. The absence of normal muscle atonia during REM sleep describes the presentation of dream-enacting behaviors suggestive of REM sleep behavior disorder (RBD). RBD has been recognized as a potential prodrome to neurodegenerative diseases including Parkinson's disease (PD), and early detection and intervention are important for patient management [1]–[4]. The purpose of this review is to present a thorough summary on the methods and techniques used for REM sleep behavior disorder detection. It addresses advantages and limitations of different diagnostics analyzes as well as an ethical and moral view on early detection in neurodegenerative diseases.

Inclusion of existing data aside, these tools, platforms and services should also enhance diagnosis and clinical decision support. And they have to include smart human-computer interface solutions for easier daily use in clinical work. Any type of medical information (textual, number quantification values, signal recordings, images) that relates to a certain pathology can be used [5], [6]. The aim is to ensure that the patient and healthcare providers are at the heart of developing solutions and channel them towards well-defined patient and public sector needs. In accordance with current international standards and laws, it is important that ethical and legal issues are carefully considered [7]. This includes collecting relevant evidence for healthcare professionals and patients to make informed decisions, while ensuring that data safety is given the utmost importance. There are various advantages if digitalize system for the diagnosis of neurological disorder is adopted. Some of these benefits include:

a. Improved diagnosis and treatment of neurological disorders: By implementing a digitalized electroencephalogram (EEG) recording system, healthcare professionals would be able to more accurately diagnose and treat neurological disorders, such as epilepsy, by having access to high-quality EEG data. The integration of this technology involves a systematic recording procedure as shown in Figure 1, where brain potentials are measured and processed for clinical evaluation.
b. Lower healthcare costs: The shift in the EEG recording process to digital would probably prompt a more accurate and efficient diagnosis, which can help in reducing the cost of side effects due to misdiagnosis and unfavorable medication.
c. Accessibility to healthcare: Using digital EEG recording machine and systems, medical experts could be able to easily and quickly access and analyze EEG data; concluding in enhancing accessibility of healthcare for the citizens of Oman; in specific those living in poor or remote areas.
d. Better patient outcomes: As a result of timely and more accurate diagnosis or treatment, individuals with neurologic diseases are likely to have improved outcomes.

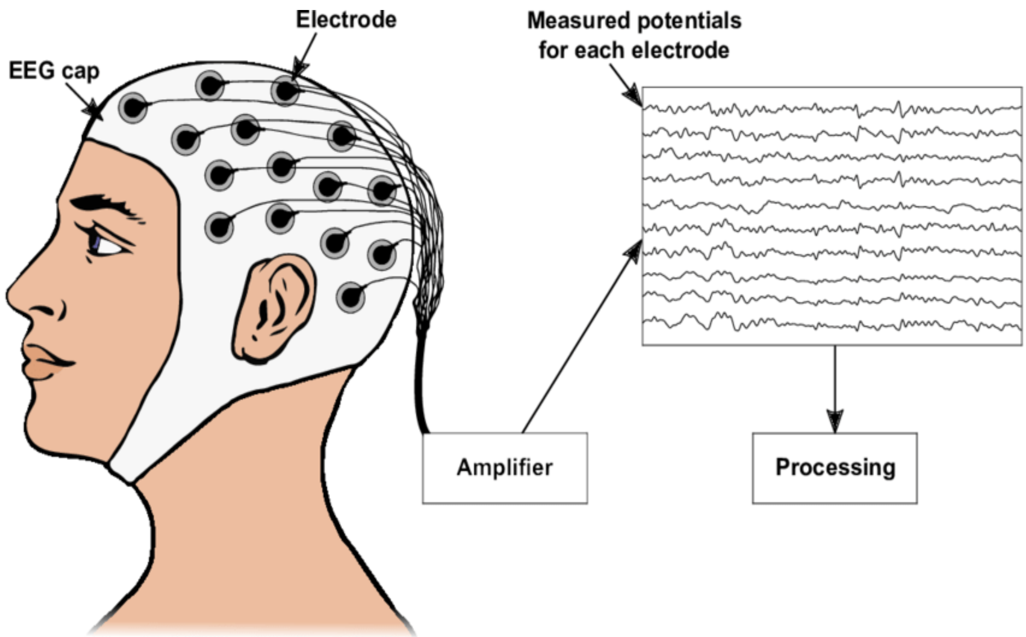

Figure 1. EEG recording procedure and monitor [7]

2. LITERTURE SURVEY

The studies included specifically concern novel progress within the field of study, focusing on methodologies, technologies, datasets, and results implemented or achieved by previous authors. The contributions of these validated papers are summarized in the following Table 1, providing a structured and comparative analysis that will help to identify existing knowledge gaps as well as future research opportunities [8]–[16].

Table 1. Summary of recent studies on RBD detection methodologies, datasets, and performance outcomes

Authors (Year)	Dataset/Subjects	Method (signals and algorithm)	Key outcome (s)/Performance	Notes/Strengths and limitations
Cooray *et al.* [8] (2019)	53 RBD+53 age-matched controls (PSG).	Automated PSG pipeline (EEG, EOG, EMG) + Random Forest classifier (156 features).	RBD detection accuracy 96% (with manual staging); 92% using automated staging.	Strong automated pipeline; shows feasibility of translation to wearable/home tech. Slight performance drop with automated staging.
Cooray *et al.* [9] (2021)	50 RBD+50 controls (PSG).	Minimal sensors (EOG+EMG ± ECG), Random Forest for 3-state staging + RBD metrics.	RBD detection accuracy ≈0.90 ± 0.11; sensitivity ≈0.88; specificity ≈0.92.	Cost-effective minimal sensor approach suitable for screening; lower staging kappa without EEG.
Röthenbacher *et al.* [10] (2022) - RBDtector	174 subjects (102 RBD, 72 non-RBD) + validation sets.	Open-source software to score RSWA per SINBAR visual criteria; EMG (mentalis, FDS, AT).	Using combined channels RBDtector achieved sensitivity 96% and specificity 100% (reported cut-offs) in dataset comparisons.	Provides an open, reproducible implementation of SINBAR scoring; helps standardize RSWA quantification. Nature
Perslev *et al.* [11] (2021) - U-Sleep	Multiple clinical PSG datasets (trained on 15,660 participants).	U-Sleep deep learning framework for automatic high-frequency sleep staging (EEG/EOG combinations).	High-quality automated staging comparable to expert scorers; robust across channel combinations. Useful as upstream staging for RBD detection pipelines.	Highly generalizable automatic staging model; supports variable channel montages—good for research/clinical pipelines.
Högl *et al.* [12] (2018) - review/update	Multicenter clinical data (review).	Review of biomarkers, PSG, imaging, autonomic and neurophys markers in idiopathic RBD.	Summarizes diagnostic standards; emphasizes PSG (video-PSG) and RSWA as key diagnostic markers.	Authoritative review; places RBD in prodromal α-synucleinopathy context. Not a detection-algorithm paper, but important clinical background.
Postuma *et al.* [13] 2019	Large multicenter iRBD cohort (longitudinal).	Clinical, neurophysiological follow-up to estimate phenoconversion to PD/DLB/MSA.	Confirms iRBD as a powerful early marker for Parkinsonism/dementia; provides predictors of phenoconversion.	Important for linking detection to clinical outcome/justification for screening.
Frauscher *et al.* [14] 2008	17 patients (idiopathic RBD and RBD secondary to PD) — multi-muscle EMG PSG.	Quantification of phasic EMG across multiple muscles during REM.	Identified best muscle combinations (mentalis+FDS+EDB) to detect phasic EMG activity; provides quantitative EMG baseline data.	One of the earlier quantitative EMG studies establishing which muscles best capture RWA. Small sample size.
Sasai-Sakuma *et al.* [15] 2014	PSG dataset (clinical).	Quantitative assessment of isolated RWA using refined EMG cut-offs (SINBAR-related).	Showed some subjects with incidental RWA meet quantitative cut-offs for RBD; highlighted need for longitudinal follow-up.	Supports use of quantitative EMG thresholds; suggests importance for early detection.
Puligheddu *et al.* [16] (2023) - review	Review of RSWA scoring methods (literature).	Systematic discussion of RSWA scoring approaches, metrics, and variability.	Summarizes available scoring methods and calls for harmonization and standard cut-offs.	Useful recent review focusing specifically on RSWA quantification—relevant for algorithm developers and clinicians.

Abbreviations:
EOG: Electro-oculography, RSWA: REM-sleep without atonia, FDS: flexor digitorum superficialis, AT: anterior tibialis, RWA: REM without atonia, PD: Parkinson's disease, DLB: dementia with Lewy bodies, MSA: multiple system atrophy

We have seen significant progress in RBD detection and evaluation. Quantitative electromyography (EMG) measures for the diagnosis of REM sleep without atonia (RWA) were determined in earlier seminal studies, providing benchmark values and ensuing normative criteria. Following clinical studies and multicenter studies demonstrated the striking relationship between idiopathic RBD and neurodegenerative diseases, highlighting the critical significance of timely and precise diagnosis [17]–[19].

Recent work has shown a move towards automation, machine learning and less sensors to yield efficient solutions of screening diagnosis at scale. Although deep-learning models and automated algorithms based on polysomnography (PSG) exhibit good performance, they have a potential for improvement when facing pathological underpinning such as Parkinson's disease–associated RBD. Wearable technologies show promise for large-scale monitoring, but are not currently as aetiologic stand-alone diagnostics. Overall, the reviewed studies collectively underscore the need for reliable, automated, and clinically practical RBD detection systems that balance accuracy, accessibility, and scalability. These insights directly inform the motivation for developing improved methodologies for early diagnosis and long-term monitoring.

3. METHOD AND METHODOLOGY

This chapter provides the systematic procedure used in our study to achieve sound analysis, prove results and repeatability of findings. The method is constructed from well-established research procedures including data acquisition, preprocessing and analytical techniques with result interpretation. A predefined method was used for clarity, consistency and scientific rigor.

3.1. Clinical assessment of RBD

Quantitative information in an EEG signal is difficult to obtain. It is so since it is the inter-and intra-brain (internal/external) information processing that mandates those EEG dynamics. On the shorter time scale, from ten to twenty seconds, such non-stationary (high pass) filtered EEG can be accounted for in terms of basic stochastic properties. We should now view the signal spectrum as a set of stationary random processes to be determined.

a. Polysomnography (PSG): PSG is the gold standard of diagnosing sleep disorders and requires overnight monitoring of various physiological features during sleep including brain wave activity, eye movement and muscle tone. Reliability of PSG for detection of RBD and distinguishing RBD from other sleep disorders the paper then reviews the data on the reliability of PSG in detecting RBD and its ability to differentiate it from other parasomnias during sleep [20], [21].
b. Clinical history and questionnaires: A detailed clinical history taking along with the use of specific questionnaires continues to be essential for the diagnosis of RBD. This article discusses the sensitivity of different questionnaires and clinical interviews in escalating symptoms of RBD [22]–[24].
c. Actigraphy: The use of wrist-worn devices has become welcome tools for measuring sleep–wake pattern accelerometer. This section reviews actigraphy for detection of RBD episodes and its application in the clinical practice routine [25]–[27].
d. Video monitoring and home sleep studies: The development of video monitoring technology and the possibility of home sleep studies offer possibilities for low-cost RBD detection which are convenient to the patients [28], [29].

3.2. The processing of cyclic alternating pattern sleep EEG data

The analysis is conducted using MATLAB. Following initial processing, power spectral density (PSD) is calculated for all sleep stages (S0-S4, REM). A one-minute clipped EEG signal is employed for different sleep stages, with DC offset removed, and filtered data is subjected to a Hanning window with 50% overlapping [30].

The trapezoidal method is employed for estimating normalized and average power. Normalized power values for EEG data components reveal distinct ranges for healthy subjects and those with various sleep disorders. The research relies on a subject database maintained by the National Institute of General Medical Sciences (NIGMS), USA, and the National Institute of Biomedical Imaging and Bioengineering (NIBIB), USA, under NIH grant number 2R01GM104987-09 [31].

Physio bank collections, comprising 108 polysomnographic recordings, each containing subject information, are utilized. EEG activity during non-rapid eye movement (NREM) sleep is characterized as periodic cyclic alternating pattern (CAP) data. The study involves sixteen healthy subjects without neurological disorders or drug use. Ninety-two pathological recordings include individuals diagnosed with various conditions such as nocturnal frontal lobe epilepsy (NFLE), RBD, periodic leg movements (PLM), insomnia, narcolepsy, sleep-disordered breathing (SDB), and Bruxism.

3.3. EEG data recording

The input for the analysis comprises the entire EEG signal recorded throughout the night, inclusive of sleep events. The sleep events are isolated from this comprehensive dataset, resulting in individual clipped signals. Each of these clipped signals corresponds to a distinct stage of sleep. Figure 2 describes different EEG recording signals, illustrating the extracted data signals after the isolation of sleep events from the input, this result use in my research work [32]. Figure 2 shows the EEG signal which has multiple channels (Fp2 –F4, C4-A1, ROC-LOC and others) of a single stage of sleep REM. Extracted different channels from EEG data C4-A1 channels are shown in Figure 3.

3.4. Algorithm and implementation

The development of an algorithm for the detection of sleep disorders and its implementation in MATLAB, together with the creation of a prototype EEG recording equipment [33]–[35], required the collection of electroencephalograms (EEG) from normal participants as well as various types of patients with sleep problems [36], [37]. After EEG data processing, a healthy subject's normalized power range is established. This number is used as a guide for identifying various sleep disorders. For each stage of sleep, PSD calculations are made [31], [38]. One minute of a clipped EEG signal is used, which contains information from channels indicating various phases of sleep [39].

Data with DC offset removed is filtered, passed through a Hamming window with 50% overlap, and the average and standard deviation are calculated using the trapezoidal technique [40]. EEG wave components (Delta (1-4 Hz), Theta (4-6 Hz), Alpha (8-13 Hz), and Beta (13-25 Hz)) [38] calculated normalized and average power of signal spectra are used to suggest the likelihood of identifying various types of neurological illnesses [41]. This approach can quickly analyze a vast quantity of data since the comparison results provide an accurate estimation of PSD for various neurological conditions. For each stage of sleep, the PSD is analyzed and calculated. The findings firmly support the potential of identifying various types of neurological illnesses (RBD, insomnia, SDB and others). The comprehensive step-by-step procedure developed in this study, ranging from signal preprocessing to the classification of sleep disorders, is visually summarized in the flow chart presented in Figure 4. An algorithm used in this thesis for the detection of sleep disorders.

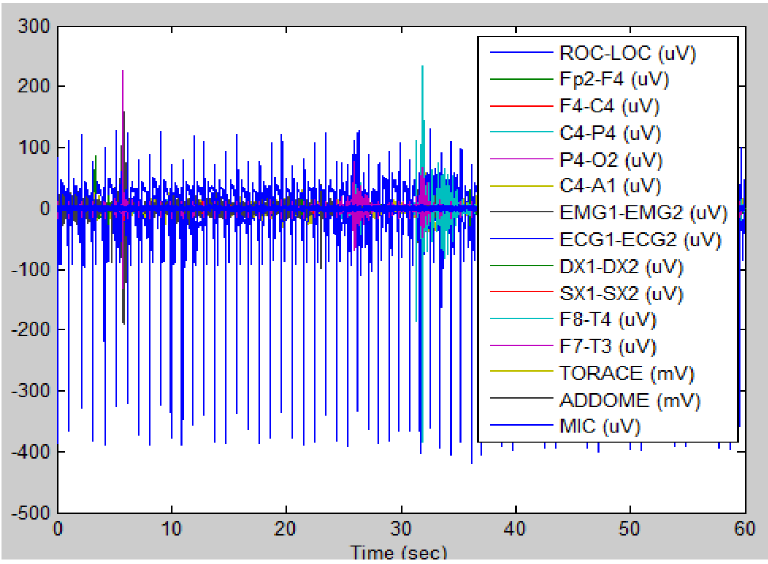

Figure 2. EEG_RBD recording using all channel for REM stage of sleep

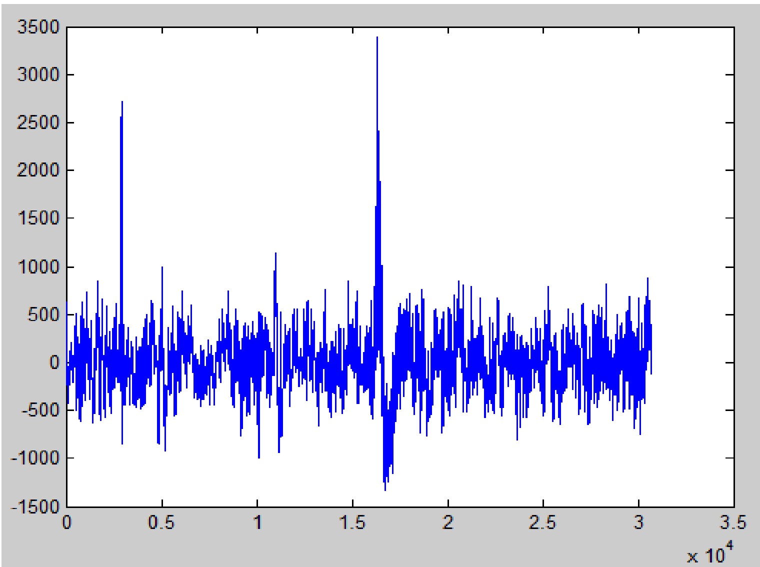

Figure 3. EEG_RBD recording with_C4-A1 channel (REM stage)

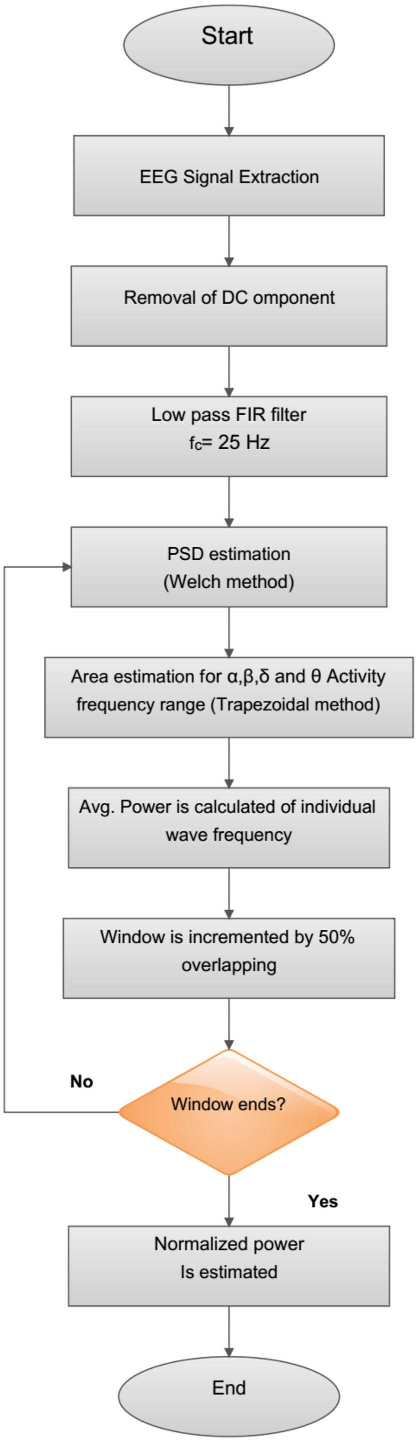

Figure 4. Flow chart for detection of sleep disorders

4. RESULTS AND DISCUSSION

Figure 5 illustrates discernible differences in normalized power between normal patients and those experiencing RBD Disorder. This distinction in beta wave normalized power between normal subjects and those with RBD underscores a noteworthy pattern. In normal RBD the range is relatively higher, in between 0.0010 to 0.0049, whereas it remained significantly lower than the one of RBD: (from 0.0076 to 014). These differences in normalized power values indicate a possible connection between the beta wave activity and whether RBD is present. Additional examination and interpretation of these findings will help in enhancing the comprehension of the neurophysiology related to REM behavior disorder.

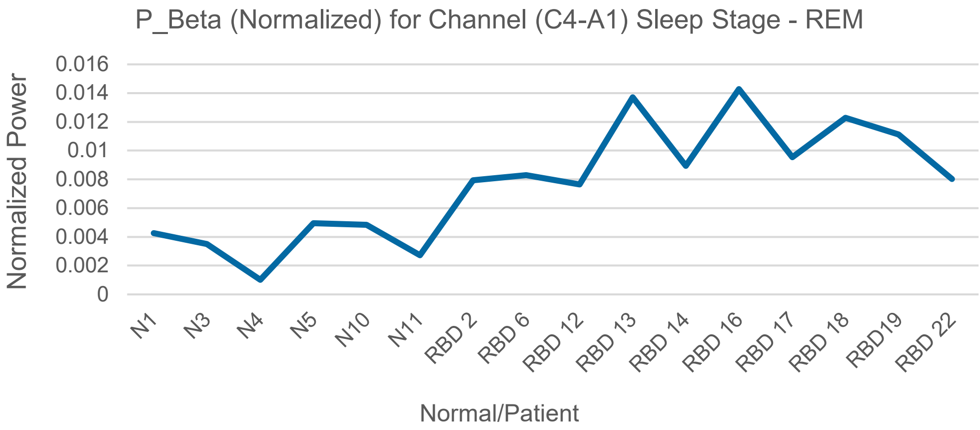

Figure 5. The Beta wave_EEG signal (normalized power) for both the normal subject and the RBD patient, focusing on the C4-A1 channel during the REM stage

Moreover, the difference shown in Figure 6 in observed disparity in beta wave normalized power not only points to a quantitative difference but also suggests potential clinical significance. The normal range of 0.0020-0.0089 for healthy subjects reflects an accustomed and typical pattern, while the markedly higher order of magnitude at 0.053-0.0791 in RBD patients indicates deviation from this standard tendency. Interestingly the targeted study of the EEG signal in the REM stage, especially at C4-A1 and EMG1-EMG2 channels, appears as a key in these results. The normalized power of beta wave is further confirmed as a unique index, evidencing its effectiveness in discriminating between normal- and rapid eye movement behavior disorder sufferers.

The significance of examiner the individual channels and EEG features in the diagnosis workup of sleep disorder is highlighted, with the normalized power of beta wave demonstrating its potency as a discriminative factor. Additional studies and validation may improve precision and reliability on how to use these results in the clinical setting.

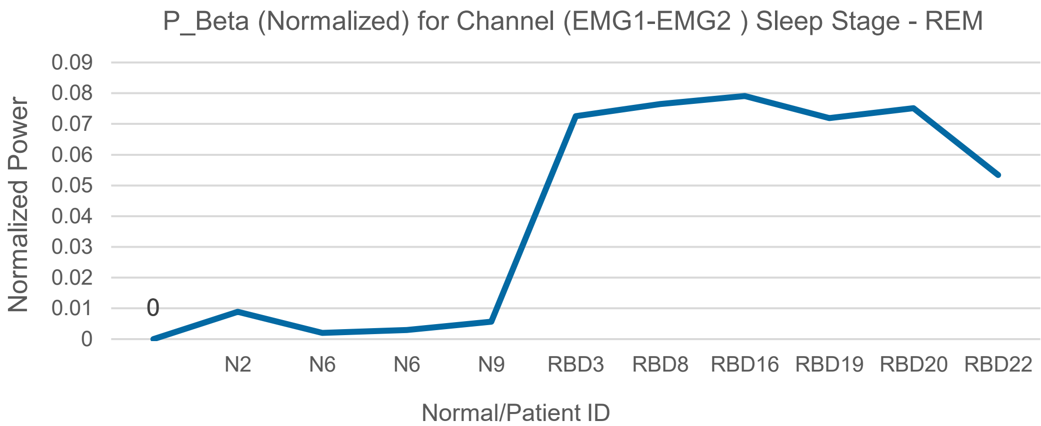

Figure 6. The Beta wave_EEG signal (normalized power) for both the normal subject and the RBD patient, focusing on the EMG1-EMG2 channel during the REM stage

5. CONCLUSION

The calculation of normalized power in the sample population of patients without symptoms sleep disorders and setting reference values is compared to pathologically impaired individuals. Namely, a voltage magnitude range is described and focused mainly on S0, S1 and REM stage of sleep. Of these, only ROC-LOC, C4-A1, and EMG1-EMG2 channels are involved in the power constraint computation over the meaningful frequency band of EEG signals among 21 channels which normal EEG data typically contains. The normalized power is calculated as a ratio of each EEG activity to the total power.

It is observed that index utilizing PSD gives better indication for feature recognition than directly using average power of each EEG activity. The results facilitate a clear differentiation between individuals with sleep disorders and those without, based on normalized power. This methodology presents an alternative to the contemporary graphical method of detection, offering economic advantages by reducing the need for a full-time expert in data analysis. The implementation of this approach requires only computer literacy, making it accessible to a broader range of individuals

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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

All the database sleep disorders and also for other diseases databases, are available here *https://physionet.org/content/capslpdb/1.0.0/*.

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BIOGRAPHIES OF AUTHORS

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