2023 IEEE Symposium Series on Computational Intelligence (SSCI)
Mexico City, Mexico. December 5-8, 2023

Quantitative Quality Assessment for EEG Data: A Mini Review

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***Abstract*—Electroencephalography (EEG) is an essential neuromonitoring modality, deeply integrated across scientific disciplines such as psychology, cognitive science, computational neuroscience, neurology, and psychiatry. Its relevance has surged with the rise of brain-computer interfaces. However, the potential of non-invasive EEG is hindered by compromised signal quality compared to invasive methods. The distinction between the modest EEG source amplitudes and the pronounced magnitudes of non-EEG physiological signals and environmental interferences complicates the analysis. The coexistence of subtle neural signals and prominent artifacts, both intrinsic and acquired, characterizes EEG signal processing. Various artifact management techniques have been proposed, yet the pursuit of EEG signal quality assessment remains underexplored. This mini-review addresses this gap by emphasizing the vital role of quality assessment in EEG recordings. The article highlights the significance of rigorous signal evaluation, emphasizing reliable EEG data. It also encapsulates evolving quantitative methodologies that bolster signal fidelity assessment. By delving into these aspects, the article presents a compact overview of ongoing advancements in quantitative EEG quality assessment techniques in the research field of EEG analysis and applications.**

***Index Terms*—EEG, Artifact, Quality assessment**

I. Introduction

Electroencephalography (EEG), often simply referred to as EEG, plays a crucial role in the realm of neuromonitoring. It functions by capturing the fluctuations in the electrical field on the scalp, providing a means to observe brain activity in action. The unique characteristics of EEG include its high temporal resolution, capable of tracking events on the order of milliseconds, and its modest spatial resolution, enabling the study of macroscopic cortical brain activities and neural oscillations. These neural oscillations reflect the synchronized firing of a multitude of neurons, offering insights into the brain's functional dynamics [1].

Spanning the domains of physiology, psychology, cognitive science, neurology, psychiatry, etc, EEG has emerged as a versatile tool with applications that touch upon a wide spectrum of scientific disciplines [2]. Of particular note are its clinical applications, where EEG serves as a cost-effective diagnostic support mechanism compared to more intricate techniques like Magnetoencephalography (MEG) or functional Magnetic Resonance Imaging (fMRI) [3]. Within this context of diverse applications, the proliferation of brain-computer interfaces has positioned EEG at the forefront of contemporary investigation. The ability to interface with computers through brain activity has ushered in a new era of research and practical applications, further amplifying the relevance of EEG in modern scientific exploration.

Nonetheless, a critical challenge looms in the domain of non-invasive EEG. This approach grapples with inherent limitations that result in diminished signal quality when contrasted with invasive alternatives. Notably, the amplitude of EEG signals falls short when compared to the potency exhibited by non-EEG physiological signals, such as those generated by eye movements and muscle activity, which could dominate the recorded data. The presence of environmental interferences further compounds this challenge, forging a landscape characterized by the juxtaposition of feeble neural signals and conspicuous artifacts [4].

In response, researchers have devised various strategies to mitigate these artifacts and enhance data quality. Nevertheless, the aspect of EEG quality assessment remains relatively underdeveloped in comparison. While methods for artifact removal abound, the rigorous evaluation of data integrity remains a crucial, yet often overlooked, aspect of the EEG analysis process [5]. This is the focal point of the present article, which seeks to illuminate the paramount significance of thorough quality assessment in the context of EEG recordings. By advocating for a comprehensive evaluation of data quality, the article endeavors to encapsulate the evolving landscape of quantitative methodologies designed to ensure the fidelity and reliability of EEG data.

II. Time-Locked EEG Responses

Event-related potentials (ERPs), a fundamental aspect of EEG applications, play a pivotal role in diverse research domains. ERPs manifest as subtle voltage changes or electrophysiological responses triggered by specific events or stimuli, reflecting the collective activity of postsynaptic potentials resulting from the firing of numerous similarly oriented cortical pyramidal neurons [6]. Their distinctive characteristics, marked by latency and amplitude, are closely tied to the experimental design [7].

ERPs encompass a range of specific waveforms, each associated with a distinct experimental context. They are categorized into exogenous or sensory ERPs and endogenous or cognitive ERPs. Exogenous ERPs primarily depend on the physical attributes of events, typically peaking within approximately 100 milliseconds post-event onset. In contrast, endogenous ERPs surface later, often shedding light on how subjects process and assess events [7].

Notable among these components is the P50 component, characterized by a prominent positive peak occurring between

This work was supported in part by the National Science and Technology Council (NSTC) under Contracts 109-2222-E-009-006-MY3, 110-2221-E-A49-130-MY2, 110-2314-B-037-061, 112-2321-B-A49-012, and 112-2222-E-A49-008-MY2; and in part by the Higher Education Sprout Project of National Yang Ming Chiao Tung University and Ministry of Education. Corresponding author: Chun-Shu Wei (wei@nycu.edu.tw).

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40 and 75 milliseconds after the onset of conditioning events. It is commonly evoked through the ”steady-state” paradigm. The N100 component emerges in response to unexpected stimuli, appearing as a negative deflection between 90 and 200 milliseconds post-event onset. The P300 component, a positive deflection emerging between 300 and 400 milliseconds following stimulus onset, holds significance dating back to 1965. Its latency is indicative of mental performance, with shorter latencies associated with superior cognitive processing. Notably, higher attention levels result in larger P300 amplitudes. Paradigms such as the ”oddball” paradigm, where infrequent stimuli appear within a series, are commonly employed to elicit the P300 component.

ERPs play a pivotal role in understanding cognitive processes, neural responses, and mental states. Extracting ERPs from EEG recordings necessitates techniques to enhance the signal-to-noise ratio (SNR). The average method is widely utilized, leveraging the assumption of a fixed time delay between events and evoked activities. This approach enhances the discernibility of ERP signals from background noise, facilitating accurate analysis.

III. Rhythmic EEG Activities

In contrast to the time-locked EEG activity discussed previously, rhythmic EEG activity, such as motor imagery (MI) EEG, offers an exploration into endogenous evoked responses, specifically elicited through subjective consciousness [8]. Motor imagery is a cognitive process wherein individuals envision movement without physically executing it, or flexing their muscles. The elusive nature of motor imagery lies in its occurrence and onset time, which are intricate to detect. In the realm of MI EEG research, event-related synchronization (ERS) and event-related desynchronization (ERD) [9] are central phenomena that highlight frequency-specific alterations. These phenomena are prominently discussed when exploring MI EEG.

The act of imagining movement, whether of the left or right hand, prompts the emergence of ERD in the subject-specific band power within contralateral sensorimotor areas, concomitant with ERS on the ipsilateral side [10]. This distinctive manifestation of EEG activity during motor imagery underscores the intricate interplay between cognitive processes and neural oscillations.

Motor imagery has garnered significant attention in the context of sports rehabilitation and cognitive neuroscience. It serves as a powerful tool to study cognitive mechanisms associated with movement planning, execution, and motor learning. The identification and decoding of motor imagery-related EEG patterns have applications in brain-computer interfaces (BCIs) for assistive technology, where individuals can control external devices using their neural signals [11].

IV. Task-Irrelevant EEG Signals

In addition to above-mentioned task-relevant EEG, task-irrelevant EEG activity finds utility in clinical applications. An example of task-irrelevant EEG is resting state EEG, which has garnered attention due to its link to various cognitive functions, as substantiated by substantial evidence [12]. Resting state EEG studies play a pivotal role in assessing intrinsic neural activity that emerges in the absence of specific tasks or stimuli. This facet of EEG investigation is particularly significant in unraveling the brain’s inherent dynamics.

Resting-state EEG often finds synergy with resting-state functional magnetic resonance imaging (rs-fMRI) in connectivity studies conducted during rest. This symbiotic relationship between EEG and fMRI enables comprehensive insights into resting-state neural connectivity, particularly in contexts like epilepsy and sleep disorders [13]. The advantages and limitations of each method complement each other, enhancing the comprehensiveness of the observations made.

Resting state EEG has applications beyond clinical realms. It serves as a valuable tool for probing the functional organization of the brain, highlighting patterns of neural synchronization that persist even in the absence of explicit tasks or stimuli. This provides a window into the brain’s intrinsic network architecture and can uncover alterations in neural connectivity associated with various neurological and psychiatric conditions [14].

V. Artifacts in EEG Recordings

EEG recordings can be tainted by artifacts, extraneous elements that distort or obscure the genuine EEG patterns. These artifacts emanate from diverse sources and are broadly classified into two categories: Physiological and Non-Physiological [1].

A. Physiological Artifacts

Physiological artifacts stem from electric-dipole-like sources within the body or the inherent biological properties of the subject. Consequently, EEG recordings invariably include these artifacts, making their distinction and removal a significant challenge. A prevalent physiological artifact arises from ocular activities, including vertical eye blinks and the electroretinogram. Other physiological artifacts, such as glossokinestic (oropharynx), cardiogenic (heart), and myogenic (muscle), exhibit distinct waveforms that experts can discern [15].

B. Non-Physiological Artifacts

Non-physiological artifacts emerge from various sources and locations within the EEG recording system, encompassing environmental influences and electrical devices in proximity to the subject [16]. These artifacts exhibit diverse morphologies, which can distort or obscure genuine EEG patterns, potentially rendering recordings incomprehensible.

1) Electrode and Connections: Among the commonly encountered non-physiological artifacts, electrode-related issues stand out. Mismatched or high-impedance electrodes, salt bridges, and electrode-related anomalies like ”pops” or lead wire sways can compromise data integrity [17]. Such artifacts may result from broken lead wires, inadequate electrode gel contact, or faulty electrode pin connections.

2) Instrumental Artifact: Malfunctioning recording instruments contribute significantly to artifact generation. Amplifier circuit thermal noise can introduce amplifier noise, intensifying with the amplifier's bandwidth. Additionally, inadequate sampling rates of EEG machines can yield artifacts. Excessive 50/60-Hz powerline noise can arise from power supply defects or poor connections. Digital recording might lead to inaccuracies during analog-to-digital conversion, resulting in data loss or "sticky" bits. The proximity of digital instruments can trigger instrumental artifacts, mimicking high-frequency oscillations during power cycling.

3) Main Power Supply: Alternating interference from the main power supply constitutes a prevalent source of instrumental artifacts. The frequency of these artifacts differs between the United States (60 Hz) and Europe (50 Hz). While notched filters can mitigate excessive 50/60-Hz noise, widespread occurrence across recording channels might signal issues with ground electrodes or EEG machine grounding.

4) Electromagnetic Artifacts: Electromagnetic Artifacts: Even when inactive, portable and cellular telephones can introduce artifacts into EEG recordings [18]. Noise stemming from non-cerebral activities during recording significantly impacts EEG signal quality.

VI. EEG Preprocessing and Artifact Removal

The enhancement of electroencephalography (EEG) data quality rests upon the precision of preprocessing and the efficacy of artifact removal methods. Unlike a rigid "standard" approach, designing an EEG preprocessing pipeline is contingent on the specific research objectives at hand. Nevertheless, dedicated automatic preprocessing pipelines have emerged, tailored to address the unique demands of distinct EEG contexts. Noteworthy among these are the PREP framework [19] and HAPPE [20], developed with a focus on enhancing EEG data quality for resting-state EEG and event-related potentials (ERP) studies. The common preprocessing methods that underpin EEG data quality enhancement include but are not limited to the following techniques:

A. Centering

Channel-wise de-meaning, referred to as centering, is a pivotal step in EEG preprocessing, particularly for recordings exhibiting a significant direct current (DC) offset effect. This technique effectively eliminates baseline shifts, priming the data for subsequent analyses.

B. Average Re-Reference

The average re-reference method, a form of offline referencing, involves transforming data to a common reference point, often an earlobe. This approach gains traction, especially when the electrode montage comprehensively covers the entire scalp. It aids in reducing the influence of non-neural artifacts.

C. Filtering

A cornerstone of EEG preprocessing, filtering tailors the EEG data to align with the study's research objectives. Finite Impulse Response (FIR) filters provide diverse designs, encompassing low-pass, high-pass, and band-pass configurations. A distinctive characteristic of FIR filters is their consistent group delay across frequency ranges. In contrast, Infinite Impulse Response (IIR) filters introduce non-linear phase shifts, yielding variable group delays with frequency.

D. Artifact Subspace Reconstruction (ASR)

ASR is an automatic and non-stationary method for artifact removal. It excels in eliminating transient or high-amplitude artifacts by harnessing Infinite Impulse Response (IIR) filters and Cholesky vectorization. ASR constructively eradicates artifacts that may otherwise distort EEG data [21].

E. Independent Component Analysis (ICA)

ICA stands as a stationary artifact removal technique, operating under the assumption that brain source signals are statistically independent. ICA's versatility is exemplified through multiple model formalizations, each governed by distinct constraints [22]. This method is particularly proficient in discerning complex mixtures of neural and non-neural signals.

The choice and implementation of these techniques hinge upon the precise research context and the inherent nature of the EEG data. Specific research contexts, such as resting-state EEG or event-related potentials, warrant tailored preprocessing strategies. While these techniques substantially elevate data quality, their utilization demands expertise in interpretation and validation to ensure genuine neural signals remain intact while artifacts are successfully eliminated.

VII. Quality Assessment for EEG Data

The assessment of EEG signal quality represents a nascent but pivotal dimension in the realm of brain-computer interfaces. As highlighted earlier, EEG data inherently encompasses artifacts that hold the potential to confound the interpretation of genuine brain activities, particularly when analyzed by non-experts. Traditionally, EEG data acquired under the aegis of qualified professionals has been perceived as artifact-reduced, mitigating the risk of noise contamination. However, a paradigm shift has emerged, with researchers increasingly attuning to the existence of anomalous EEG waveforms during experiments, which underscores the fundamental role of EEG signal quality assessment.

Concurrently, many researchers engage in post-experiment offline quality assessment, involving the examination of raw EEG data waveforms through EEG-analysis software. While these methods serve as initial and intuitive benchmarks, they may introduce subjectivity in both resting and task-related EEG recordings. The evaluation of signal quality within this context hinges on the expertise of the evaluator.

This section embarks on a multifaceted exploration, commencing with an examination of the literature pertaining to EEG signal quality assessment—a thematic continuation from the preceding sections. Subsequently, we delve into an appraisal of inter-subject and intra-subject variabilities, foundational components underpinning our research assumptions.

The final phase of this discourse encapsulates the impetus propelling our study.

A. Impedance Assessment

In addition to the aforementioned subjective methodologies, the impedance-based assessment is a common EEG signal quality evaluation technique. This method gauges the quality of EEG signal acquisition by measuring the impedance between the electrodes and the skin tissue. An optimal signal acquisition process necessitates low impedance between the electrodes and the tissue, ensuring that the input impedance of the amplifier significantly surpasses the input impedance between the electrodes and the skin. For conventional scalp electrodes facilitated by electrolytic paste, it is recommended that impedance remains below $10k\Omega$ to ensure effective electrode connectivity. Notably, researchers have examined the impact of impedance on EEG signal quality, positing that higher impedance might compromise signal fidelity relative to lower impedance settings. Consequently, numerous studies focusing on the impedance method as a measure of EEG signal quality assessment have surfaced. For instance, Kappenman and Luck [23] observed that high-impedance sites exhibit increased low-frequency noise compared to low-impedance sites during an oddball task. Traditionally, researchers have sought to mitigate noise and artifacts by minimizing impedance between electrodes and the skin tissue [24], [25].

B. Signal-to-Noise Ratio (SNR) Assessment

The SNR has served as a prevalent index for EEG signal quality assessment across various applications. In ERP waveform analysis, SNR assumes diverse forms, such as peak amplitude [26]. Particularly in ERP-related investigations, the accurate identification of ERPs hinges on SNR-enhanced methods due to the relatively lower magnitude of ERPs in contrast to the background ongoing EEG activity [27]. These methods necessitate the repetition of the event of interest in a sufficient quantity. The time domain average is one of the widely employed techniques, as previously introduced: EEG recordings are segmented into epochs according to defined time intervals encompassing the onset of the event of interest. Subsequently, all epochs are averaged to generate a consolidated waveform.

C. Statistical Methodology

Fickling et al. [28] have proposed a statistical method consisting of six metrics collectively termed the EEG Quality Index, devised for quality assessment and artifact detection. The EEG recording is divided into segments through a sliding window approach with a 1-second duration and half-second overlap. The metrics encompass various aspects of the EEG signal. The first metric quantifies the average single-sided amplitude spectrum by computing the mean absolute value of the Fast Fourier Transform (FFT) in the 1 to 50 Hz frequency band, encapsulating delta, theta, alpha, beta, and low gamma waves. Similarly, the Line noise average single-sided amplitude spectrum, the second metric, is computed in the frequency band of 59 to 61 Hz. Other metrics include the RMS Amplitude, which gauges signal magnitude across the window, the Maximum Gradient denoting the maximum difference between adjacent time points, Zero-Crossing Rate quantifying the average difference of sgn function values of adjacent time points, and Kurtosis, a standard statistical measure reflecting the tails' distribution heaviness.

D. Variability Assessment

The assessment of variability assumes significance in both intra-subject and inter-subject contexts. Intra-subject variability denotes the variations in sample points within the same subject, while inter-subject variability pertains to variations across different subjects. Inter-subject variability has notably surfaced as a challenge in ERP experiments, with the P300 component being a prominent point of discussion. This component has demonstrated substantial variability among subjects [29], [30]. Recent research by Li et al. [31] endeavors to uncover neural substrates that underpin the inter-subject variability of the P300 component. Their study explores the brain's transition from the resting state to the P300 component during visual oddball tasks, elucidating mechanisms facilitating efficient information processing. Furthermore, the researchers sought to predict individual performance through brain reconfiguration, highlighting how inter-subject variability in both resting and task-related stages effectively directs individual behaviors. This research provides insights into BCI performance variations and uncovers potential biomarkers for personalized control within brain-computer interfaces.

VIII. Challenges and Future Directions

The journey through EEG signal quality assessment reveals several challenges that warrant attention. The dichotomy between physiological and non-physiological artifacts presents a complex landscape where different artifact types interact, potentially complicating the removal process. While automated preprocessing pipelines like PREP and HAPPE streamline the initial stages of quality assessment, they might not comprehensively address all artifact types [32]. Therefore, further research is required to develop hybrid approaches that combine various methods to achieve optimal artifact removal.

Moreover, the subjectivity inherent in some quality assessment methods, such as visual inspection, demands solutions that enhance objectivity. The application of machine learning algorithms, pattern recognition techniques, and data-driven analyses could contribute to more quantifiable and reproducible quality assessment measures [33]. Integrating these advances into the existing methodologies could usher in a new era of objective quality assessment.

IX. Conclusion

EEG data quality augmentation pivots on judicious preprocessing and adept artifact removal. Techniques such as centering, average re-reference, and an array of filtering methodologies refine the raw EEG data, while advanced methods such as ASR autonomously combat artifacts, thus elevating the neural data's integrity. The development of quantitative quality assessment methods for EEG data is a dynamic and evolving field, driven by the imperative to extract meaningful neural information from complex and artifact-laden signals. These methodologies not only enhance the interpretation of EEG recordings but also facilitate advancements in brain-computer interfaces, cognitive neuroscience, and clinical research.

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