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Neural oscillations and pain modulation following invasive procedures: A review of EEG based insights

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Abstract
The current understanding of pain, particularly postoperative pain, integrates both physiological and psychological dimensions, as highlighted by the IASP's widely accepted definition. Despite advances in clinical practices, postoperative pain remains highly variable, influenced by numerous factors including individual pain thresholds, procedural techniques, and preoperative conditions. Recent research in neural oscillations and EEG technologies has provided valuable insight into brain activity related to pain perception. Notably, alpha wave activity, particularly oscillations below 9 Hz, has shown promise as a predictive biomarker for severe postoperative pain. This finding opens avenues for proactive pain management strategies.
EEG, especially in its portable and mobile forms, has become a pivotal non-invasive modality for assessing neural activity in real-world and clinical settings. Through time-frequency analysis and correction techniques like dB conversion, EEG data offer a robust means to study cognitive and sensory processes, including pain perception. The correlation between alpha oscillations and pain sensitivity underscores the brain's role in shaping pain experiences and highlights the potential of EEG-based tools in predicting and managing postoperative pain. As portable EEG technologies evolve, their integration into clinical workflows could enable personalized pain interventions, reducing the risk of chronic pain development and improving patient outcomes.

Keywords: EEG, neural oscillations, modulation, management strategies, improving patient outcomes

Introduction
Pain is a multifaceted sensory and emotional phenomenon characterized by significant inter-individual variability. Notably, the perception of pain is intimately associated with neural oscillatory activity, which is essential for the coordination and integration of functional brain networks [1]. A substantial body of research on both acute and chronic pain, utilizing Electroencephalography (EEG) and Magneto Encephalography (MEG), has underscored the significant involvement of neural oscillations across theta, alpha, beta, and gamma frequency bands in shaping pain perception. However, the specificity of this association remains a subject of debate. Broadly, the link between pain perception and neural oscillatory activity can be categorized into three principal dimensions [2].

First, nociceptive stimuli elicit marked alterations in neural oscillatory activity across the theta, alpha, beta, and gamma frequency bands, with the amplitude of certain oscillatory changes showing a strong correlation with the subjective intensity of pain perception. Second, pre-stimulus neural oscillatory patterns have been found to predict the perceived pain severity elicited by subsequent nociceptive input. Third, dysregulated neural oscillations are commonly recordered in individuals with chronic pain conditions [3].

Pain
The prevailing definition of pain, formulated by the International Association for the Study of Pain (IASP) as 'an unpleasant sensory and emotional experience associated with actual or potential tissue damage, or described in terms of such damage,' was proposed by the Subcommittee on Taxonomy and officially adopted by the IASP Council in 1979.

This definition has gained widespread acceptance among clinicians and pain researchers and has been endorsed by numerous professional, governmental, and non-governmental organizations, including the World Health Organization [4].

Postoperative pain prevalence and severity

The reported occurrence of postoperative pain within the initial 24 to 48 hours following surgery varies widely, ranging from 3% to 69.3% [5]. While some studies have documented mild to moderate postoperative pain, others have reported moderate to severe intensity. Additionally, several investigations noted the occurrence of severe pain within 12 to 24 hours after the procedure. Postoperative discomfort generally persists for 24 to 48 hours; however, in certain cases, patients experience pain extending for 3 to 9 days following root canal therapy. The observed variability in findings may be attributed to differences in the criteria used for pain assessment, variations in the materials and techniques employed during root canal procedures, and the frequent omission of preoperative pain as a contributing factor [6].

Neural Oscillations

Brain rhythms, or neural oscillations, denote the rhythmic fluctuations in neural population activity as measured by local field potentials (LFPs), electroencephalography (EEG), or magnetoencephalography (MEG). These oscillations are typically observed within the 1-100 Hz frequency range and arise from the dynamic balance between excitatory and inhibitory neuronal processes, resulting in the periodic synchronization of action potentials. Moreover, functional magnetic resonance imaging (fMRI) has identified infraslow brain activity fluctuations occurring at frequencies below 0.1 Hz [7].

Neural activity can exhibit synchronization at any frequency, occurring both within localized brain regions and across distributed networks [8]. Brain oscillations have been related to a wide range of perceptual, cognitive, and behavioral processes. Consequently, interpretations of their functional roles have differed considerably across experimental paradigms and disciplinary perspectives. More recently, however, these diverse viewpoints have been integrated within a cohesive physiological framework, suggesting that brain oscillations play a mechanistic function in dynamically directing the flow of information within neural networks [9].

This conceptual framework is grounded in converging anatomical and functional evidence from both animal models and human studies. Anatomical pathways within the visual system are clearly delineated into feed forward (bottom-up) and feedback (top-down) circuits [10].

This anatomical differentiation is mirrored in the laminar distribution of feed forward and feedback projections within the cortex. Feed forward connections generally originate from supragranular layers and terminate in layer IV, while feedback pathways predominantly arise from infragranular layers and project to cortical layers excluding layer IV. Moreover, this asymmetrical structural organization corresponds to a similarly non-uniform pattern of neural oscillations across cortical layers. Empirical studies have demonstrated that alpha and beta band oscillations (8-29 Hz) are more pronounced in infragranular layers, whereas gamma band activity (~30-100 Hz) is typically more prominent in the supragranular layers [11].

Given the previously described laminar organization of cortical connections, a functional association has been proposed linking feed forward signaling with gamma-band oscillations and feedback signaling with alpha/beta-band activity. This hypothesis has been supported by recent empirical evidence. A study employing magneto-encephalography (MEG) to examine human visual cortical areas utilized measures of directed connectivity, such as Granger causality, to characterize information flow. The findings revealed stronger gamma-band connectivity in the feed forward direction from lower to higher-order visual areas while feedback connectivity, from higher to lower-order areas, was predominantly observed in the alpha and beta frequency ranges [12].

EEG

EEG is a noninvasive neuroimaging method that records the brain's electrical activity through electrodes positioned on the scalp [13]. EEG represents a signal pattern derived from the amplification and recording of spontaneous brain-generated bioelectrical potentials at the scalp. These potentials reflect large-scale neural activity across the cortical surface and are typically measured by means of noninvasive electrodes placed on the scalp. The electrodes detect rhythmic and endogenous electrical discharges produced by synchronized activity within populations of neurons [14, 15].

EEG waveform classification

EEG signal frequency, expressed in Hertz (Hz), denotes the number of waveform cycles occurring per unit of time. EEG activity is traditionally categorized into five primary frequency bands: Delta (0.5-4 Hz), Theta (4-8 Hz), Alpha (8-13 Hz), Beta (13-30 Hz), and Gamma (> 30 Hz). Delta waves are characteristic of deep sleep and slow-wave brain activity; Theta waves are typically observed during states of relaxation and meditation; Alpha waves are most prominent with closed eyes and a relaxed but alert mental state; Beta waves are related to active cognitive processing and heightened attentional demands and Gamma waves are related with higher-order cognitive functions and multisensory integration. EEG channels are systematically labeled based on their anatomical placement relative to the midline and the anterior-posterior axis of the scalp. These channels enable the assessment of electrical brain activity across different cortical regions, providing valuable insights into cognitive functions as attention, memory, and emotional processing [16, 17].

Alpha Activity of EEG

A reduction in alpha activity, particularly within the parieto-occipital regions, has been the most frequently reported alteration in EEG findings [18].

However, some researchers have documented conflicting results. For instance, Le Pera *et al*. observed an elevation in alpha activity over the parietal regions, Bobiloni *et al*. noted elevated activity in the frontal area contralateral to the site of stimulation, and Martel *et al*. reported increased alpha activity in the prefrontal region ipsilateral to the stimulation [19].

Alpha oscillations in EEG have attracted significant attention due to their proposed involvement in various cognitive, sensorimotor, emotional, and physiological processes. Despite this interest, there remains a lack of consensus regarding the precise functional significance of alpha activity, as well as the most appropriate metrics for its characterization. Terminological ambiguities further complicate interpretation; for example, the phrase 'alpha rhythm is activated' is unclear, as it does not specify whether this denotes fluctuation in amplitude. Similar uncertainty arises when attempting to quantify terms such as 'prominent rhythm,' 'organized EEG,' 'flat EEG,' or 'regular oscillations,' highlighting the need for more standardized definitions and measurement criteria [20].

Alpha waves role in prediction the postoperative pain

The study demonstrated a robust association between patients' alpha brain wave activity and their postoperative pain responses. Specifically, individuals exhibiting preoperative alpha oscillations below 9 Hz were significantly more susceptible to experiencing acute postoperative pain. Remarkably, the preoperative alpha frequency was able to predict with 100% accuracy which patients would report a postoperative pain score of seven or more on a ten-point scale [21].

Dr. Ali Mazaheri, senior author of the study and a researcher at the Centre for Human Brain Health and the School of Psychology at the University of Birmingham, emphasized that while pain is a complex and subjective experience, alpha oscillations appear to serve as a reliable biomarker for predicting the severity of an individual's pain perception [21].

This provides clinicians with a potentially valuable biomarker for anticipating and mitigating pain before it escalates into a severe or chronic condition, rather than addressing it only after it has become established [21].

Electroencephalography's biophysics and measurement

EEG has become a standard non-invasive tool to track and analyzing neural electrical activity in the human brain [22]. EEG has broad applications across multiple domains, including the diagnosis of neurological conditions, sleep disorders, focal brain abnormalities, and functional brain mapping. The development of advanced EEG technologies has significantly transformed the field by facilitating real-time monitoring of brain activity [23]. To improve accessibility and address the limitations related to cost and limited adaptability of conventional EEG systems, a new class of portable devices referred to as mobile-EEG has been developed [24]. The emergence of these mobile systems has enabled more practical and efficient real-time monitoring of neural activity [25].

Portable EEG Devices

Portable EEG technology (PEEGT) typically provides a wireless, ergonomic, cost-effective, and non-invasive solution for monitoring brain activity, making it accessible to both researchers and general users interested in exploring the neural correlates of behavior and cognitive processes. Increasingly, PEEGT is being adopted as a research tool within the field of education, suggesting its potential relevance for advancing educational research. Nevertheless, this proposition requires further validation through practical implementation and, more importantly, through the accumulation of robust empirical evidence [26].

In recent years, the use of mobile and portable devices capable of monitoring various aspects of daily activity has seen a marked increase. In particular, the demand for brainwave monitoring beyond clinical settings has highlighted the need for affordable, portable, and wearable EEG systems. Mobile Brain/Body Imaging (MoBI) technology has been developed to meet this demand by enabling the simultaneous recording of brain activity, bodily dynamics, and both exogenous and endogenous events, thereby enabling a deeper insight of brain function in naturalistic environments. Although portable EEG systems are primarily utilized for extended-duration signal recording, they are also capable of functioning as real-time monitoring platforms, including remote controlled or remotely observed configurations [27].

These devices are frequently integrated with Brain Computer Interface (BCI) systems that utilize real-time signal processing algorithms to visualize the dynamic patterns of brainwave activity. Typically, such systems capture raw EEG signals associated with motor imagery from various cortical regions, including the frontal, parietal, temporal, and occipital lobes. The integration of a head-mounted display enables the development of autonomous EEG-based BCI systems, which have been successfully demonstrated in applications such as three dimensional spatial navigation and visual field evaluation [28]. The emergence of user-friendly, wearable EEG/BCI technologies eliminating the need for traditional gel-based and cumbersome setups has catalyzed a growing trend toward brain-driven interaction with external software and hardware systems, as well as the widespread acquisition of brain and cognitive health data in real-world environments [29].

Time-frequency analysis (TFA) of electrophysiological data

Since the inception of EEG, the investigation of rhythmic neural activity commonly referred to as neural oscillations has remained a fundamental focus in neuroscience. Oscillatory activity across a range of frequencies has been implicated in nearly every domain of cognition, including perception, attention, and memory processes [30].

Techniques for detecting narrowband oscillations commonly involve transforming neural signals into the frequency or time-frequency domain, wherein oscillatory activity is identified by spectral peaks or localized power increases within the time frequency representation. Notably, neural data in these domains typically exhibit a $1/f$-like power spectrum, characterized by a decrease in amplitude and consequently power as frequency increases, in accordance with a power law distribution. This spectral property is thought to reflect irregular, non-periodic neuronal or population-level firing, which contrasts with the structured, rhythmic activity that defines true neural oscillations [31].

Although broadband activity arising from non-oscillatory sources is commonly labeled as $1/f$ 'noise,' accumulating evidence suggests that it may carry functional relevance for behavioral performance [32]. Throughout this manuscript, we will use the terms '$1/f$ activity' and '$1/f$ noise' interchangeably to denote broadband neural activity. This terminology choice reflects the convention in studies focused on narrowband oscillatory dynamics, where 1/f components are generally not the primary focus. In fact, in such analyses, $1/f$ noise is typically accounted for either in the frequency or time frequency domain to prevent it from confounding narrowband power estimates, masking genuine differences in oscillatory activity across frequency bands, or producing spurious effects [33, 34].

As previously discussed, a common approach to detecting narrowband neural phenomena involves transforming electrophysiological signals into the time frequency domain a technique that has gained considerable traction over the past two decades. This analytic method enables the investigation of temporal fluctuations in spectral content, such as changes occurring before and after stimulus presentation. In studies employing this approach, a widely used strategy for addressing the ubiquitous $1/f$ power distribution involves baseline correction of raw power values (typically expressed in μV^2). This is achieved by dividing each time point by the average power within a predefined baseline period often preceding the stimulus at each frequency. The resulting normalized values are subsequently converted into decibel (dB) units by applying a base-10 logarithmic transformation and multiplying by 10These steps are summarized by the following formula [35]

$$\mathrm{dB(activity)_{tf}} = 10 \times \log_{10}\left(\frac{activity_{tf}}{baseline\ activity_f}\right)$$

In this context, *t* represents the time point of interest, and *f* denotes a specific frequency. The widespread use of decibel (dB) conversion as a baseline correction method is exemplified by its implementation as the default option in the *newtimef()* function of the widely used EEGLAB toolbox [36].

As previously noted, applying dB conversion to time frequency decomposed neural data involves two nonlinear operations division by a baseline spectrum followed by logarithmic transformation. This process is mathematically equivalent to first applying a logarithmic transformation to the power values and then subtracting the corresponding baseline values. The rationale for the log-transformation lies in the inherent positive skew of power distributions; converting these values to a logarithmic scale produces more symmetrical, approximately normal distributions. Such distributional properties are advantageous for statistical analyses aimed at testing hypotheses concerning changes in power as a function of experimental variables [36].

Conflict of Interest

Not available

Financial Support

Not available

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