Time-Frequency Analysis of Cognitive Processes

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Date: 2019-10-14T00:00:00+00:00

Abstract

Time-frequency analysis represents a relatively novel analytical technique that offers unique advantages through its ability to provide additional information and enable cross-species comparisons. However, it is currently underutilized in most EEG studies, thereby failing to further explore the deeper implications of power across different frequency bands during task responses. Consequently, reinterpreting time-frequency analysis and its reported results holds substantial value. Furthermore, through comparative analysis of publication volumes, the relative scarcity and profound significance of time-frequency analysis in cognitive process research are once again underscored. By proceeding from the significance of time-frequency analysis and focusing on result presentation and interpretation, this provides researchers with an alternative framework for conducting EEG research.

Full Text

Time-Frequency Analysis in Cognitive Process Research

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Abstract

Time-frequency analysis represents a relatively novel analytical technique that offers unique advantages by providing richer information and enabling cross-species comparisons. However, most current EEG studies have not incorporated time-frequency analysis, thereby failing to uncover the deeper significance of energy fluctuations across different frequency bands during task performance. Consequently, a re-examination of time-frequency analysis and its result reporting holds substantial value. Through comparisons of publication volumes, this paper further emphasizes the relative scarcity yet profound importance of time-frequency analysis in cognitive process research. Beginning with the significance of time-frequency analysis and focusing on result presentation and interpretation, this article provides researchers with an alternative framework for conducting EEG studies.

Keywords: Time-frequency analysis; Cognitive process; Energy band; Result interpretation

Introduction

Cognitive processes unfold over brief timescales, and electroencephalography (EEG) offers superior temporal resolution compared to other neuroimaging modalities, making it a preferred tool for cognitive research. EEG is a technique that records population-level bioelectric activity from neuronal ensembles at the scalp, amplifying these signals to produce continuous waveforms (Schomer & Da Silva, 2012). Initially, EEG analysis relied solely on clinicians' experiential judgment for diagnostic purposes. In 1932, Dietch pioneered the application of Fourier transform to EEG analysis, enabling quantitative approaches to brain signal processing (Litt & Echauz, 2002). This development led to time-domain analyses such as event-related potentials (ERPs), which employ methods like hypothesis testing on mean amplitudes within specific time windows (Lachaux et al., 2000). Complementing these approaches, frequency-domain analysis primarily utilizes power spectral and correlation analyses (Nunez et al., 1997). However, ERPs cannot adequately disentangle additive activity from phase resetting (Wu, Zhong, Ding, & Qu, 2018), and neither time- nor frequency-domain analyses alone fully exploit the information contained in EEG signals. Time-frequency analysis provides a solution for more comprehensive information utilization.

To analyze event-related EEG changes and understand cognitive processes, researchers typically employ ERP methods. Some scholars propose that each ERP component can be conceptualized as event-related neural oscillations at specific frequencies or as superpositions of multiple oscillations across different frequencies (Herrmann, Rach, Vosskuhl, & Struber, 2014; W. Klimesch, Sauseng, Hanslmayr, Gruber, & Freunberger, 2007; Makeig et al., 2002). Evidence indicates that pre-stimulus spontaneous oscillations can influence the amplitude and latency of post-stimulus ERP components. For instance, alpha-range oscillations modulate the N1 component, with larger N1 amplitudes associated with shorter reaction times (Barry et al., 2004; Haig & Gordon, 1998). Similarly, theta oscillations have been identified as primary contributors to the P300 component (Yordanova & Kolev, 1998). Although ERPs may not be entirely composed of neural oscillations as some researchers suggest (Risner, Aura, Black, & Gawne, 2009; Sauseng et al., 2007), the importance of time-frequency analysis in EEG research is undeniable. Nevertheless, psychological researchers frequently overlook time-frequency analysis, thereby forgoing opportunities to obtain richer information. Given this neglect and its potential value, a comprehensive review of time-frequency analysis techniques is warranted, along with a synthesis of how to interpret results from a cognitive process perspective.

The Significance of Time-Frequency Analysis

Time-frequency analysis (TFA), as the name suggests, is a technique that simultaneously considers both temporal and spectral signal characteristics, representing signals as time-frequency density functions (L. Cohen, 1995; Sejdic, Djurovic, & Jiang, 2009). While not applicable to all research questions, TFA's multidimensional approach—treating frequency as a prominent dimension—enables cross-disciplinary and cross-species investigations. Time-frequency analysis offers three key advantages. First, its results can be interpreted through the lens of neural oscillation mechanisms, which represent a fundamental and ubiquitous neural mechanism supporting diverse functions across synaptic, cellular, and systems levels in both space and time (Varela, Lachaux, Rodriguez, & Martinerie, 2001). Second, this neurophysiological foundation makes neural oscillations the most likely bridge connecting findings across neuroscience domains and species, as they can be studied in healthy humans using scalp EEG, in human patients using intracranial recordings, and in non-human animals using in vivo microelectrodes. Third, from a practical statistical standpoint, while ERPs reveal only partial information, time-frequency analysis uncovers additional task-related dynamics that event-related analyses alone cannot capture. For researchers primarily interested in cognitive processes, TFA can provide more accurate answers, particularly when information is non-phase-locked. In summary, time-frequency analysis facilitates comparative research and enables the acquisition and application of richer information. Despite certain limitations —such as potential reductions in temporal precision and analytical challenges stemming from insufficient guidance on parameter selection and interpretation —these drawbacks are often overstated. Some ERP studies employ temporal resolutions comparable to those used in TFA, and the complexity of analysis, while demanding, should not deter its application (M. X. Cohen, 2014).

Time-frequency analysis typically yields three types of results: frequency, power, and phase. Frequency refers to oscillation speed measured in Hertz (Hz), power represents oscillatory energy (the square of amplitude), and phase describes the position at any given time point in radians or degrees.

Overview of Time-Frequency Research

To examine trends in time-frequency analysis applications, we compared publication data with ERP studies using PubMed annual analyses from January 1 to December 31 each year. The results show that while TFA publications have increased year-over-year, ERP publications have followed an inverted U-shaped trajectory. However, due to its relatively recent emergence and the difficulty of interpreting some cognitive processes (M. X. Cohen, 2014), TFA literature remains substantially less abundant than ERP literature, underscoring the need for greater researcher attention.

Within China, time-frequency analysis has been sparsely utilized, primarily in pathological research such as epilepsy studies (Gong et al., 2018; Wang, Hu, &

Wang, 2018). Nevertheless, some studies have interpreted TFA results from a cognitive perspective. For example, research has shown that distrust decisions elicit more negative N2 components and smaller P3 components compared to trust decisions, while the gain context induces larger beta-band activity (Fu, 2018). Additionally, researchers have found that insight stages can be distinguished through time-frequency characteristics (Shen, Liu, Zhang, & Zhang, 2012).

Analytical Methods

EEG fundamentally records time-domain signals comprising spontaneous neural oscillations, random noise, and desired event-related electrical changes. While converting signals entirely to the frequency domain clarifies spectral content, it sacrifices temporal information. Time-frequency analysis offers a compromise solution. An ideal time-frequency analysis should feature high resolution in both time and frequency domains, minimal cross-term interference to distinguish true components from noise, and reduced computational complexity to ensure efficient signal processing.

Current TFA predominantly employs wavelet transforms to reveal the temporal evolution of spectral components (Bartnik, Blinowska, & Durka, 1992). Although short-time Fourier transform or multiple bandpass filters combined with Hilbert transform represent alternative approaches, wavelet analysis has gained widespread adoption due to its computational efficiency, reduced cross-terms, analysis windows that match the biological reality of brief high-frequency and prolonged low-frequency events, and more reasonable underlying assumptions (Mishra, Martinez, Schroeder, & Hillyard, 2012). Wavelet transform operates on the principle of allowing temporal variation while maintaining shape consistency through appropriate basis function selection. However, limitations exist: wavelet frequencies cannot exceed half the sampling rate, and frequency smoothing due to the time-frequency precision trade-off means closely adjacent frequencies yield nearly identical results. While wavelet transforms are commonly used for power calculations across frequency bands, Hilbert transform is primarily employed for phase computation (Wu et al., 2018).

Result Presentation and Interpretation

Presentation and Interpretation Steps Cohen (2014) proposed a systematic approach for result presentation and interpretation. First, determine the content to display, which most commonly includes frequency characteristics but may also encompass phase clustering, connectivity, or correlations with behavioral outcomes. Second, verify that axes represent correct time and frequency ranges. Third, examine the results for multiple activity time windows, determine whether activity is band-limited or spans multiple frequencies, and assess whether effects are localized when derived from multiple electrodes. Fourth, connect results to experimental design by reflecting on manipulations, reconsidering result significance, and comparing with prior research to summarize cognitive processes and underlying neural mechanisms. Fifth, consider statistical significance: when results do not reach significance thresholds, qualitative rather than quantitative interpretation is appropriate. Additionally, the choice between data-driven and hypothesis-driven analyses may require different analytical approaches and interpretations, as hypothesis-driven research enhances sensitivity and theoretical relevance.

Interpreting Frequency Bands Time-frequency analysis yields power, phase, and frequency information, though neuroscientists typically emphasize power. To illustrate potential results and interpretations, we review event-related neural oscillation research.

The first discovered and most well-known frequency band is alpha activity (8-12 Hz), detectable in occipital regions during relaxed wakefulness and increasing with eyes closed (Foster, Sutterer, Serences, Vogel, & Awh, 2017). Other bands include delta (1-4 Hz), theta (4-8 Hz), beta (13-30 Hz), low gamma (30-70 Hz), and high gamma (70-150 Hz), with faster rhythms like gamma activity associated with cognitive processing.

Delta Oscillations: Most notably associated with sleep, stages three and four are defined by whether delta activity exceeds 50% of the EEG record. These stages were later merged into N3 slow-wave sleep (N3 SWS), characterized by delta waves comprising 20% or more of the EEG (Berry, 2018). Sustained delta oscillations reduce interference by suppressing networks that should remain inactive during task performance (Harmony, 2013). In sensorimotor regions, beta-band (15-30 Hz) amplitude during motor planning is modulated by the number of possible targets (Tzagarakis, Ince, Leuthold, & Pellizzer, 2010), their spatial configuration (Grent-' t-Jong, Oostenveld, Jensen, Medendorp, & Praamstra, 2014), and target direction uncertainty (Tzagarakis, West, & Pellizzer, 2015). Extensive evidence linking delta oscillations to autonomic and metabolic processes suggests their involvement in integrating brain activity with homeostatic processes (Knyazev, 2012).

Theta Oscillations: Due to historical reasons, theta oscillations are divided into "hippocampal theta" and "human cortical theta," giving the term two distinct meanings. Hippocampal theta refers to regular oscillations observed in the hippocampus and connected regions, commonly studied in animal research. Human cortical theta denotes 4-7 Hz oscillations regardless of location or functional significance, typically investigated in human studies. Human theta oscillations are generally associated with memory processes (W. Klimesch, 1999), tending to increase during memory tasks, particularly during encoding. When subjects process stimuli requiring attentional resources, ERPs show the P3 component, which is primarily composed of delta and theta oscillations (Basareroglu, Basar, Demiralp, & Schurmann, 1992; Yordanova, Kolev, & Kirov, 2012). Additionally, cortical theta rhythms are frequently associated with cognitive control processes (Anguera et al., 2013; Cavanagh, Zambrano-Vazquez, & Allen, 2012).

Alpha Oscillations: Discovered by EEG inventor Hans Berger, alpha was the first waveform recorded, with beta following shortly after. Berger showed interest in "alpha blocking," the process of alpha wave reduction. In honor of his discovery, alpha waves are also called "Berger' s Waves" (Berger, 1929). Historically, alpha was considered to represent idle visual cortex activity, more prominent during eyes-closed rest. This association with task disengagement has strongly influenced how researchers interpret alpha amplitude (or "power") changes observed across numerous studies. Alpha oscillations correlate negatively with cognitive performance, suggesting inhibition of task-irrelevant cortical structures (Ole Jensen & Mazaheri, 2010). Alpha power changes also predict attentional demands; for example, cues indicating upcoming auditory stimuli produce greater occipitoparietal (visual) cortex alpha increases compared to cues for visual stimuli (Foxe, Simpson, & Ahlfors, 1998; Fu et al., 2001). Thus, elevated alpha power represents neglect or inattention to objects or locations (Knakker, Weiss, & Vidnyã, 2014; Snyder & Foxe, 2010). When maintaining information in visual working memory, alpha power typically increases to prevent memory content from being disrupted by irrelevant visual input (O. Jensen, Gelfand, Kounios, & Lisman, 2002). Overall, research indicates alpha oscillations reflect memory (Bonnefond & Jensen, 2012; Wolfgang Klimesch, 1997) and attentional processes (Hanslmayr, Gross, Klimesch, & Shapiro, 2011). Recent proposals suggest treating alpha as a family of functions serving as inhibitor, perceiver, predictor, communicator, and stabilizer (Clayton, Yeung, & Cohen Kadosh, 2018). Transcranial alternating current stimulation (tACS) studies demonstrate that alpha oscillations facilitate cognitive control and perceptual stability with visual specificity, as auditory stimulation does not produce similar effects (Clayton, Yeung, & Cohen Kadosh, 2019).

Beta Oscillations: Beta waves are neural oscillations in the 12.5-30 Hz range, sometimes subdivided into low beta (12.5-16 Hz, "Beta 1 power"), beta (16.5-20 Hz, "Beta 2 power"), and high beta (20.5-28 Hz, "Beta 3 power") (Rangaswamy et al., 2002). Historically associated with alert wakefulness, beta oscillations are prominently modulated during motor task execution (Neuper & Pfurtscheller, 2001) and observed in cognitive tasks requiring sensorimotor interaction (Kilavik, Zaepffel, Brovelli, MacKay, & Riehle, 2013), such as sensorimotor integration (Baker, 2007). Beta oscillations can be modulated by motor planning or reward expectation (Kilavik et al., 2013) and are implicated in learning and memory (Gnaedinger, Gurden, Gourevitch, & Martin, 2019; Fellner et al., 2019). Beta activity also relates to cognitive control and attention; successful inhibition trials in stop-signal tasks produce stronger beta-band power than response trials or failed inhibition trials (Marco-Pallarés, Camara, Münte, & Rodríguez-Fornells, 2008), with maximal effects over central regions (Kopell, Whittington, & Kramer, 2011).

Gamma Oscillations: A prominent theory posits that gamma waves are associated with conscious perception (Siegle, Pritchett, & Moore, 2014; W Singer & Gray, 1995), though this remains contested (Vanderwolf, 2000). Gamma oscillations are closely linked to detailed information processing (Fries, Reynolds, Rorie, & Desimone, 2001; Womelsdorf & Fries, 2006) and active maintenance of memory contents (Herrmann, Munk, & Engel, 2004). Research also demonstrates gamma-band involvement in feature binding during both perception (Busch, Herrmann, Müller, Daniel, & Thomas, 2006; Gruber, Tsivilis, Giabbiconi, & Muller, 2008; Tallon, 2009) and encoding stages (Morgan et al., 2011; Tseng, Chang, Chang, Liang, & Juan, 2016). Recent findings indicate that gamma amplitude is modulated by spatial attention across cortical hierarchies, including early visual cortex and higher-order regions of the ventral visual pathway (Magazzini & Singh, 2018).

Conclusion and Future Directions

Although simple time-domain ERP analysis remains more common in cognitive research due to its early development, time-frequency analysis' s capacity for cross-species comparison and its closer approximation to neural mechanisms will make it an increasingly essential analytical tool. TFA enables researchers to obtain richer information and develop more fundamental mechanistic explanations of cognitive processes. Reviewing recommendations for result presentation and clarifying relationships between neural oscillations and cognitive functions can guide researchers in their thinking and investigations.

Like other cognitive neuroscience approaches, time-frequency analysis should be combined with multiple methods (Berman, Kardan, Kotabe, Nusbaum, & London, 2019), incorporating brain stimulation techniques such as tDCS and tACS for causal investigations of different cognitive processes (Herrmann, Struber, Helfrich, & Engel, 2016). The persistent mysteries surrounding cross-species brain oscillation functions underscore the importance of time-frequency analysis for both human and animal model research (Colgin, 2013).

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Note: Figure translations are in progress. See original paper for figures.