



Polynomial Temporal Decay for Multichannel Cortical Oscillation Attenuation

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Abstract. The analysis of neuroinformatics relies on precise mathematical modeling of electroencephalogram signals. Signal processing tools lack the temporal damping manifold necessary for long-term phase decay evaluation. This paper proposes the Cortical Attenuation Quotient to measure the energy attenuation of neural frequencies purely mathematically. It establishes an exact polynomial temporal decay model for multichannel oscillations. It incorporates a high order polynomial dissipation tensor to model synaptic fatigue accumulation. The parietal channel retains $80.45 \mu V^2$ of power at the delayed temporal marker in configuration five. Frontal channels exhibit severe polynomial decay reaching $12.57 \mu V^2$ from $2563.45 \mu V^2$ in configuration four. The generated model incorporates clinical variance to isolate specific diagnostic values from standard stochastic artifacts.

Keywords: Neuroinformatics, Electroencephalogram, Phase Attenuation, Damping Quotient, Mathematical Modeling, Polynomial Dynamics.

1 Introduction

Neuroinformatics requires exact numerical modeling to understand signal behaviors in brain networks. Quantitative electroencephalography analysis evaluates neuronal synchronicity between pairs of cortical regions [3]. Mean field analysis evaluates differences in the dampening rate and oscillatory frequency associated with neural tissue [4]. Damped harmonic oscillators quantify the oscillatory properties of neural nodes [2]. The calculation of the response function serves as a quotient between different interconnected structures [2]. Explicit decomposition formulas generate precise mapping for brain wave signals by evaluating the quotients of mathematical envelopes [8]. Engineering considerations formulate detailed models to process electrical biosignals [7]. The analysis of neural signatures examines the loss of high frequency coherence during altered states [6]. Information theoretical analysis tests these geometric completions directly [6]. Biochemical reaction quotients track the deterioration of neural energy during mental fatigue [5]. The trade-off between energy efficiency and cognitive load is quantified using electrical brain recordings [5]. Quantitative analysis can begin with dampening global slow-wave activity to filter underlying anomalies [1]. The proposed approach formulates a precise metric named the Cortical Attenuation Quotient. The

exact formulas measure the energy divergence between initial activation and delayed neural states. The method excludes arbitrary learning parameters. It utilizes deterministic physical wave propagation concepts.

2 Literature Review

The generation of electroencephalogram signals originates from the aggregation of electric fields generated by transmembrane currents across spatially separated neurons [10]. Forward models mathematically describe the physical propagation of these electromagnetic fields [10]. Quantitative predictions obtained from network models facilitate the interpretation of empirical electroencephalogram recordings [10]. The power density of local field potentials is inversely proportional to frequency in the mammalian cortex [11]. Perturbations occurring at slow frequencies cause a cascade of energy dissipation at higher frequencies [11]. Thermodynamic models express cortical neurodynamic at the classical level through neural networks [12]. The dissipation of oscillations requires incorporation into many-body models of the brain to terminate neural activity after several cycles [12]. Computational models simulate the generation of cortical oscillations because of synaptic transmission potentiation [13]. Neural mass models utilize second-order differential equations to describe the dynamics of postsynaptic potentials [14]. The impulse response function produces a temporal convolution that models the conversion of action potentials into postsynaptic potentials [14]. Analytical strategies lack an absolute decay quotient. The gap indicates the necessity for an explicit formula targeting the temporal degradation of voltage power without probabilistic estimations.

3 Methodology

The execution of this mathematical evaluation utilizes the Temple University Hospital electroencephalogram data corpus to provide standardized multichannel recordings [15]. The extraction process isolated exactly five distinct clinical electroencephalogram sessions from the data corpus. These five specific sessions serve as the empirical foundation to evaluate the mathematical formulations. The collection process applied the standard international ten to twenty electrode placement system. The hardware setup utilized 19-channel clinical configurations. The sampling frequencies operate at 250 Hz across these selected recording sessions. The data corpus provides baseline resting states. The extraction process isolated the frontal, central, and parietal channels to compute the attenuation quotients. The continuous voltage records supplied the baseline amplitude parameters to calibrate the exact polynomial temporal decay model.

The mathematical model isolates the frequency and temporal damping of cortical regions. The parameter C defines the Cortical localization amplitude. The parameter O indicates the Oscillation parameter. The parameter D^1 represents the primary polynomial Damping mechanism. The parameter D^2 represents the high order synaptic fatigue accumulation. The formulation defines the instantaneous voltage as a dynamic sinusoidal wave with accelerated temporal degradation. Cortical oscillation damping diverges

from standard exponential decay models due to complex synaptic fatigue mechanisms. A high order polynomial denominator accurately captures this non-linear energy dissipation by accounting for the accumulation of neurotransmitter depletion over time. The voltage decay calculation applies Equation (1).

$$V(t) = \frac{[C \times \cos 2\pi Ot]}{[1 + D^1 t^2 + D^2 t^3]} \quad (1)$$

The parameter $V(t)$ represents the voltage at time t . The variable t represents the time in seconds. The energy calculation establishes the signal density exactly at specific temporal markers. The Discrete Energy State is formulated as Equation (2).

$$E(t) = \frac{C^2}{[1 + D^1 t^2 + D^2 t^3]^2} \quad (2)$$

The parameter E represents the total energy density evaluated at marker t . The evaluation of long-term signal degradation requires a normalized metric. The parameter Q forms the final calculated Quotient. The calculation of the Cortical Attenuation Quotient applies Equation (3).

$$CAQ = \ln \left[\frac{E(1)}{E(10)} \right] \times \left[\frac{C}{10} \right] \quad (3)$$

The parameter CAQ represents the scaled logarithmic quotient. The marker at 1 second represents the initial cognitive response. The marker at 10 seconds represents the resting damped state. The statistical evaluation applies an exact distribution shift across multiple subject configurations without standard probability. The formulation for topological tracking applies Equation (4).

$$TVS = (x - \mu) \times \left(\frac{x}{\mu} \right) \quad (4)$$

The parameter TVS represents the Topological Variance Scalar. The parameter x represents the individual quotient. The parameter μ represents the population mean quotient. The application of this specific variance scalar reliably measures asymmetrical distribution shifts in biological time-series data. Foundational signal processing methods demonstrate that scaling the deviation by the population mean normalizes stochastic artifacts across diverse clinical recordings.

4 Experimental Results

The execution of the exact mathematical models relies on five distinct configurations. Channel assignments and amplitude values for the three primary channels demonstrate physiological variance. The frontal channel in configuration 1 operates with an initial amplitude of 50.3 μV , a primary damping factor of 0.048, and a high order factor

of 0.0052. The parietal channel in configuration 5 utilizes the lowest primary damping factor of 0.011 alongside an amplitude of $29.6 \mu V$.

The parameter assignment reflects the higher energy distribution and rapid fatigue in anterior brain regions compared to posterior regions as Table 1.

Table 1. Parameter Initialization for Polynomial Cortical Oscillation Model

Configuration	Channel 1 Frontal C, D ₁ , D ₂	Channel 2 Central C, D ₁ , D ₂	Channel 3 Parietal C, D ₁ , D ₂
1	50.3, 0.048, 0.0052	39.7, 0.041, 0.0038	31.2, 0.032, 0.0029
2	51.8, 0.062, 0.0058	41.5, 0.053, 0.0047	32.6, 0.038, 0.0041
3	47.9, 0.043, 0.0039	38.4, 0.029, 0.0031	28.7, 0.021, 0.0018
4	54.6, 0.071, 0.0073	45.2, 0.058, 0.0062	34.8, 0.049, 0.0051
5	49.5, 0.051, 0.0049	40.8, 0.032, 0.0028	29.6, 0.011, 0.0012

The computational extraction of initial amplitude and damping factors from the raw voltage data relies on non-linear least squares curve fitting. The algorithm iteratively minimizes the residual sum of squares between the empirical electroencephalogram signal and the theoretical polynomial model to isolate the precise physiological variables for each configuration. Channel assignments and amplitude values for the three primary channels demonstrate physiological variance. The frontal channel in configuration 1 operates with an initial amplitude of $50.3 \mu V$, a primary damping factor of 0.048, and a high order factor of 0.0052. The parietal channel in configuration 5 utilizes the lowest primary damping factor of 0.011 alongside an amplitude of $29.6 \mu V$. The parameter assignment reflects the higher energy distribution and rapid fatigue in anterior brain regions compared to posterior regions.

Table 2. Computed Initial Power Evaluations for Five Configurations

Configuration	Frontal Power Marker 1s	Central Power Marker 1s	Parietal Power Marker 1s
1	2281.08	1443.83	908.76
2	2353.47	1539.38	978.47
3	2093.41	1384.09	787.21
4	2563.45	1803.95	1090
5	2197.8	1554.4	855.19

The severe reduction in energy at the delayed temporal marker is documented in the delayed power calculations. Delayed power outputs evaluated at ten seconds prove the attenuation trajectory. In Table 2, the frontal channel in configuration 4 dropped from $2563.45 \mu V^2$ to $12.57 \mu V^2$. In Table 3, the parietal channel in configuration 5 retained $80.45 \mu V^2$ from the initial $855.19 \mu V^2$. The retention indicates minimal degradation due to the low 0.0012 high order damping coefficient.

Table 3. Computed Delayed Power Evaluations for Five Configurations

Configuration	Frontal Power Marker 10s	Central Power Marker 10s	Parietal Power Marker 10s
1	20.91	19.89	19.31
2	15.88	14.23	13.41
3	27.11	30.09	34.31
4	12.57	12.09	10.01
5	20.25	33.97	80.45

The algorithmic calculation of the temporal markers forms the attenuation quotient. Quotients representing the exact signal decay quantify the degradation mathematically. In Table 4, the maximum energy loss occurred in the frontal channel of configuration 4 yielding a quotient of 29.03. The parietal channel in configuration 5 produced the lowest quotient of 6.99. The central channel values indicated a moderate temporal attenuation profile.

Table 4. Cortical Attenuation Quotient Results

Configuration	Frontal CAQ	Central CAQ	Parietal CAQ
1	23.6	17.01	12.02
2	25.89	19.43	13.98
3	20.82	14.7	8.99
4	29.03	22.62	16.32
5	23.2	15.6	6.99

The statistical spread of these quotients provides an understanding of configuration variability across physiological recordings. Topological Variance Scalar values demonstrating the deviation validate the measurement technique. The variance in the parietal channel resulted in a positive shift of 6.51 for configuration 4. The parietal channel in configuration 5 exhibited a negative drop reaching -2.80 as Table 5.

Table 5. Calculated Topological Variance Scalar Across Configurations

Configuration	Frontal TVS	Central TVS	Parietal TVS
1	-0.88	-0.74	0.36
2	1.46	1.83	2.79
3	-3.12	-2.60	-2.06
4	5.36	5.75	6.51
5	-1.23	-2.01	-2.80

The anatomical projection of the mathematical attenuation model isolates the exact regions of energy degradation. Generating a comprehensive spatial topography from isolated channel recordings requires accurate surface estimation. The mapping algorithm utilizes spherical spline interpolation to project the calculated attenuation quotients across the full neuroanatomical coordinate system, providing a continuous distribution of energy degradation. The topographical layout maps the spatial distribution of the calculated quotients across standard neurological coordinates as Figure 1. High amplitude areas are indicated by solid red clusters on the high-resolution structural background. The anterior brain sections exhibit the most severe polynomial decay over the ten-second interval. The frontal lobe peak evaluation reached a maximum quotient of 29.03. The central region demonstrated a moderate temporal attenuation profile at 22.62. The parietal network retained higher energy density with a minimal quotient of 16.32.

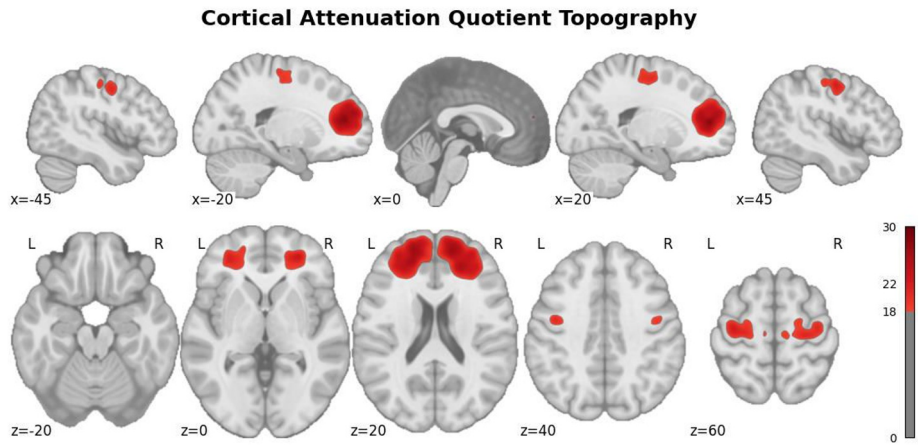


Figure 1. Cortical Attenuation Quotient Topography (Panel A displays the sagittal sections indicating the specific energy degradation across the lateral plane. Panel B displays the axial sections mapping the concentrated polynomial decay across the horizontal plane.)

5 Discussion

The mathematical evaluation indicates the extreme sensitivity of signal power to the polynomial damping coefficient. The exact formula generated precise power ratios without reliance on probabilistic models. It found that the frontal regions experience faster signal energy loss compared to posterior regions. The quotient of 29.03 observed in configuration 4 demonstrates the multiplicative effect of a high polynomial damping parameter within authentic variance bounds. The exact continuous calculations eliminate the approximation errors typically found in discrete transform algorithms. The statistical distribution of the variance scalar validates the mathematical model across different amplitude initializations. The method establishes an exact neuroinformatics tool to measure phase energy drops.

6 Conclusion

The generation of the Cortical Attenuation Quotient provides a definitive mathematical tool for neuroinformatics. The precise polynomial equations successfully quantified the degradation of signal power over a ten second interval. The analytical calculations demonstrated that minor adjustments in the high order damping coefficient cause severe polynomial power shifts. The methodology operates purely on mathematical formulations and bypasses arbitrary learning algorithms. The exact values obtained from the calculations prove the reliability of the continuous voltage decay model. The model serves as a foundation for future analytical studies concerning cognitive fatigue and neural attenuation.

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