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RESEARCH ARTICLE

Compression-Based Complexity Analysis of Thalamic EEG Using Multiscale Preprocessing Techniques

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ABSTRACT Quantifying the complexity of biomedical signals offers critical insight into underlying physiological and pathological dynamics. This study systematically evaluates compression-based complexity measures—Effort-to-Compress (ETC) and Lempel-Ziv Complexity (LZC)—and compares them with classical entropy-based metrics, including Shannon Entropy, Approximate Entropy (ApEn), Sample Entropy (SampEn), and Permutation Entropy (PermEn). Analyses were performed on both synthetic benchmark signals and clinical thalamic EEG recordings acquired during seizure and non-seizure states. Robustness was assessed under Gaussian, Laplacian, and powerline noise, with and without preprocessing via Discrete Wavelet Transform (DWT) and Differential Pulse Code Modulation (DPCM). ETC consistently demonstrated the highest discriminative power and noise resilience, achieving large effect sizes and classification accuracies exceeding 85% when combined with full-scale DWT preprocessing. In contrast, LZC performed reliably in raw data but degraded following multiscale transformations. Entropy-based measures such as SampEn and ApEn remained competitive under clean conditions yet were more sensitive to noise and preprocessing variability. These findings establish that no single complexity metric is universally optimal; rather, performance depends on signal modality, noise structure, and preprocessing design. For thalamic EEG-based seizure detection, ETC with DWT preprocessing provides a robust, interpretable, and parameter-free framework suitable for clinical and real-time neurophysiological applications.

INDEX TERMS Compression complexity, effort-to-compress (ETC), Lempel-Ziv complexity (LZC), thalamic EEG, discrete wavelet transform (DWT).

I. INTRODUCTION

Quantifying the complexity of neurophysiological signals is essential for characterizing their physiological and pathological states. In particular, thalamic electroencephalography (EEG)—enabled by stereo-EEG (sEEG)—offers unique insights into deep-brain dynamics relevant to epilepsy and consciousness [1], [2]. These signals exhibit rich temporal complexity reflecting neural activity but are also highly susceptible to physiological and environmental noise [3], [4].

Traditional analysis techniques—including spectral power estimation, threshold-based detectors, and visual inspection—have been widely used in clinical practice, yet they may fall short in capturing subtle dynamical changes that precede critical events such as epileptic seizures [5], [6].

Recent machine learning approaches applied to EEG recordings have shown promise for automated seizure detection and prediction [7], [8], [9]. However, such models

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often require extensive labeled data, computational tuning, and domain-specific feature engineering. Complexity-based methods offer an alternative: they are model-free, interpretable, and designed to quantify the intrinsic irregularity or predictability in time series data without requiring large training sets [10], [11], [12], [13].

Despite growing interest in complexity analysis of brain activity, most prior studies have focused on cortical EEG, leaving thalamic recordings relatively underexplored. The thalamus plays a central role in modulating consciousness and coordinating cortical oscillations, and is particularly relevant in epilepsy research due to its involvement in seizure propagation and generalization. Recent advances in sEEG have enabled direct thalamic recordings, opening new avenues for studying deep-brain dynamics. Yet, analytical tools for short, noisy segments of these signals remain limited. Complexity measures may offer a principled, interpretable means of quantifying dynamical changes in thalamic EEG without requiring large datasets or invasive modeling assumptions.

Among complexity metrics, symbolic and compression-based measures such as Lempel-Ziv Complexity (LZC) [14] and Effort-to-Compress (ETC) [15] have gained attention for their ability to capture nonlinear structure in physiological signals. ETC, in particular, has been shown to be robust to short data lengths and noise, offering a potential advantage over traditional entropy-based approaches [16], [17], [18], [19], [20].

While methods like the Discrete Wavelet Transform (DWT) [21] and Differential Pulse Code Modulation (DPCM) [22] are widely used for signal compression and noise reduction, they do not quantify complexity in a symbolic or algorithmic sense. Notably, our preliminary experiments revealed that applying DWT or DPCM alone does not consistently yield meaningful complexity differences between physiological states. In some cases, complexity paradoxically increased during seizure states—contrary to the well-established expectation that pathological activity typically reflects reduced variability. However, when used as a preprocessing stage, DWT in particular was found to enhance the discriminative ability of symbolic complexity measures by amplifying informative structural components. This motivates their integration as complementary preprocessing steps in complexity-based analysis pipelines [23].

In this study, we systematically evaluate the performance and robustness of compression-based complexity measures—ETC and LZC—first on synthetic signals to benchmark behavior under controlled structural variations, and then on real-world thalamic EEG recordings for seizure detection. The synthetic signals are designed to exhibit well-defined frequency or structural modulations, allowing controlled benchmarking. The thalamic EEG data offer a clinically grounded testbed for seizure versus non-seizure classification. In the EEG context, we also compare ETC and LZC with four classical entropy-based measures: Shannon Entropy, Approximate Entropy (ApEn), Sample Entropy (SampEn), and Permutation Entropy (PermEn).

We investigate three primary research questions:

1) Can compression-based complexity measures reliably distinguish between seizure and non-seizure states in thalamic EEG under noise and preprocessing?
2) Does multiscale preprocessing (e.g., DWT or DPCM) enhance the robustness and discriminative power of these measures?
3) How do ETC and LZC compare with entropy-based metrics in analyzing EEG complexity under different noise conditions?

Our results highlight the complementary strengths of compression and entropy-based complexity analysis, and demonstrate the potential of ETC as a robust and interpretable tool for neurophysiological signal characterization. To ground the interpretation of our results, we begin by revisiting a key neurophysiological principle: the reduction in complexity often observed in pathological brain states.

A. COMPLEXITY REDUCTION IN PATHOLOGICAL BRAIN STATES

A well-established neurophysiological finding is that pathological brain states are associated with reduced complexity compared to healthy conditions. In the context of epilepsy, seizure activity induces highly synchronized neuronal firing, leading to a decrease in temporal irregularity and hence reduced complexity in EEG signals [24]. This reduction in complexity serves as a robust biomarker for detecting pathological events and distinguishing them from normal physiological states. Statistically significant decreases in LZC or ETC during seizures reflect underlying physiological disruptions and hold promise for clinical monitoring applications.

B. CHALLENGES OF NOISE AND NONSTATIONARITY

While reduced complexity is often used as a marker of pathological brain dynamics, accurately estimating it in thalamic EEG recordings remains challenging. These deep-brain signals are highly susceptible to various artifacts, including motion-induced distortions and EMG contamination, which may interfere with local field potentials or mimic genuine fast activity in SEEG [25], [26], [27]. Moreover, thalamic EEG signals—like other neurophysiological recordings—are inherently nonstationary, exhibiting rapid, time-dependent variations in their statistical and spectral properties [28], [29], [30].

Such variability complicates complexity analysis: noise can spuriously inflate complexity scores, while nonstationarity may obscure meaningful physiological transitions. These challenges underscore the need for analytical frameworks that are both noise-resilient and sensitive to the intrinsic dynamics of thalamic activity across diverse physiological and pathological states.

C. THE DISCRETE WAVELET TRANSFORM: A MULTISCALE ANALYSIS TOOL

To address the limitations of direct analysis, Discrete Wavelet Transform (DWT) has emerged as a versatile tool. DWT decomposes signals into time-localized frequency components, preserving both temporal and spectral resolution simultaneously — unlike classical Fourier analysis which sacrifices temporal resolution [31], [32].

The advantages of DWT in biomedical signal analysis include:

- Multiresolution analysis: Decomposition into approximate (low-frequency) and detail (high-frequency) coefficients at multiple scales.
- Noise reduction: Effective denoising through thresholding wavelet coefficients, attenuating high-frequency noise without distorting physiological features [33].
- Feature extraction and classification: Statistical and energy-based features derived from wavelet coefficients improve classification of pathological vs. normal states in EEG signals [34].
- Image and signal compression: DWT's energy compaction property underlies standards such as JPEG 2000, enabling efficient lossy compression with minimal perceptual loss [35].

This ability to isolate physiologically relevant frequency bands makes DWT particularly valuable for analyzing complex, nonstationary biomedical signals—especially where pathologies manifest in specific spectral ranges.

While DWT is effective for extracting multiscale features and reducing noise, it does not inherently quantify signal complexity—raising the question of how it should be positioned in complexity-based analysis.

D. WHY DWT IS NOT A COMPLEXITY MEASURE

Despite its widespread utility in signal classification and compression, DWT itself is fundamentally a linear transform and cannot be considered a complexity measure. This distinction is critical:

- No intrinsic randomness quantification: Although DWT is effective for representing signal structures across scales [21], [31], it does not provide measures of algorithmic randomness, unpredictability, or minimal description length, which are central to complexity theory [36], [37].
- No direct compressibility assessment: While DWT coefficients can facilitate compression by sparsifying data, they do not measure how difficult it is to compress the original signal or its inherent complexity.
- Potential masking of complexity: By concentrating signal energy into a small set of coefficients, DWT can sometimes reduce the apparent irregularity or complexity of the signal, possibly masking important nonlinear features [15].
- Complementary role: Complexity measures like ETC and LZC estimate information complexity by assessing pattern novelty and compression effort, capturing intrinsic structural irregularities independent of signal representation [15], [38].

Therefore, DWT should be viewed as a feature extraction or preprocessing tool, not as a complexity metric.

E. COMBINING DWT AND COMPLEXITY MEASURES

Recent approaches have proposed a two-step hybrid methodology: first decompose signals with DWT to obtain multiscale coefficients, then apply complexity measures on these coefficients [39], [40], [41], [42]. This approach aims to leverage DWT's multiscale localization to isolate physiologically relevant frequency bands, enhancing sensitivity of complexity measures to pathological changes. Preliminary studies suggest that this hybrid method may outperform direct complexity analysis, particularly in seizure detection from scalp EEG. However, its efficacy in thalamic EEG analysis—especially under short-duration or noise-contaminated conditions—remains underexplored and forms the motivation for our investigation. This motivates a closer examination of complexity measures themselves, particularly LZC and ETC, in noisy and real-world signal settings.

F. RATIONALE FOR ETC AND LZC

LZC, while widely used, is known to be sensitive to noise due to its dictionary-based compression scheme, which can lead to overestimation of complexity in noisy data [38]. ETC, based on iterative pair substitution, provides improved noise robustness at the cost of increased computational effort [15]. Both measures have been used successfully in biomedical applications, but a systematic comparison of their robustness—particularly when combined with multiscale preprocessing—remains limited and motivates this study.

G. AIM OF THIS STUDY

Building on previous work that demonstrated the robustness of ETC and LZC for different applications, this study systematically evaluates the following under noise-free and noisy conditions.

- The validity of ETC and LZC as complexity measures on synthetic signals including chirp, amplitude modulated chirp, and signals with varying harmonics. These serve as controlled representations of canonical features found in real biomedical signals. For instance, chirp and AM-chirp signals simulate gradual frequency drift and amplitude variability observed in EEG and EMG; variable harmonics mimic spectral richness seen in pathological states. These controlled models allow us to evaluate the behavior of complexity measures in a noise-isolated setting before validating on real-world data.
- The ability of ETC and LZC to distinguish seizure and non-seizure states in thalamic EEG.
- The effect of DWT preprocessing on complexity-based discrimination performance.

- Comparative analysis of different DWT coefficient subsets (approximate, detail, individual decomposition levels) for complexity calculation.

Thalamic EEG, for instance, has traditionally been assessed through visual inspection, which is inherently subjective and error-prone, alongside statistical measures that, while objective, may not fully capture the complexity of underlying neural dynamics. In real time applications, the analysis can be limited by the presence of physiological noise, such as respiratory and cardiovascular artifacts, leading to false positives or negatives [43], [44], [45], [46] since they fail to capture the inherent lowering of the physiological complexity under various pathological conditions.

This work proposes the use of compression complexity based methods (ETC and LZC) for analysing thalamic EEG signals. The parallels between LZC and ETC are compared methodically in this study, highlighting the similarities between them and the potential advantages of one over the other. Further, the measured use of DWT as a pre-processing technique is explored and our results clarify the complementary role of DWT in biomedical complexity analysis, showing improved performance in thalamic EEG. Through this, our research aims to improve diagnostic and monitoring capacities in clinical settings by advancing more precise and trustworthy techniques for biological signal analysis. Taken together, this study contributes a robust and interpretable complexity analysis pipeline tailored to thalamic EEG, with potential implications for clinical monitoring and seizure detection.

The rest of this paper is organized as follows. Section II details the datasets, synthetic signal generation models, noise simulation framework, complexity measures, preprocessing techniques, and experimental design. Section III presents performance analysis across synthetic and thalamic EEG signals, with and without preprocessing and contextualizes the results in relation to other measures. Section IV discusses the effect of preprocessing with DWT, computational considerations, limitations and clinical relevance. Finally, Section V summarizes the key findings and explores possible future work.

II. MATERIALS AND METHODS

This study integrates synthetic signal models and thalamic EEG datasets to assess the robustness of compression complexity measures. The analysis spans controlled noise injections, clinically relevant perturbations, and multiscale preprocessing pipelines. Below, we outline the data sources, signal transformation strategies, complexity metrics, and evaluation procedures employed.

A. SYNTHETIC SIGNAL MODELS: CANONICAL COMPLEXITY CONSTRUCTS

We first designed idealized signal constructs to benchmark the behavior of complexity measures in response to controlled variations in frequency content, spectral richness, and envelope structure.

- **Chirp Signals:** Generated using a linear frequency sweep from 1–10 Hz over 10 seconds: $s(t) = \sin(2\pi(f_0 + kt)t)$. These emulate nonstationary oscillations commonly observed in biological dynamics [47].
- **Multi-Harmonic Signals:** Constructed as additive sinusoids with frequencies 2, 4, and 6 Hz: $s(t) = \sum_{i=1}^{3} \frac{1}{i} \sin(2\pi f_i t)$. This mimics periodic physiological rhythms such as respiration or ECG waveforms [48].
- **Amplitude-Modulated Signals (AM):** Defined as $s(t) = [1 + 0.7\sin(2\pi f_m t)] \cdot \sin(2\pi f_c t)$ with $f_m = 0.5$ Hz and $f_c = 5$ Hz. These represent respiratory-coupled oscillatory dynamics [49].

Each synthetic signal was sampled at 250 Hz for a duration of 10 sand symbolized using 4-bin discretization prior to complexity evaluation.

1) SIGNAL COMPLEXITY PROFILES

This subsection qualitatively describes the intrinsic complexity of each synthetic signal type, highlighting how structural variability affects the response of compression-based complexity measures.

a: CHIRP SIGNAL

Although chirp signals involve gradual changes in frequency, their deterministic and smooth nature makes them highly predictable. As a result, they exhibit low algorithmic complexity despite spectral evolution [50], [51].

b: AMPLITUDE-MODULATED (AM) CHIRP SIGNAL

In AM-modulated chirp signals, the superposition of amplitude fluctuations over a varying frequency sweep introduces additional temporal structure. A higher modulation index increases envelope variability, resulting in greater pattern irregularity and complexity [52], [53].

c: MULTI-HARMONIC SIGNAL

Signals composed of multiple harmonics increase the effective dimensionality of the frequency space. As the number or variability of harmonics increases, the waveform becomes less predictable and more structurally complex [31], [51], [54].

B. SYNTHETIC NOISE INJECTION

To simulate common biomedical signal artifacts, three representative noise types were injected into each synthetic signal class:

1) **Additive Gaussian White Noise (AWGN):** Simulates baseline stochastic disturbances from sensors and acquisition circuits [55].
2) **Power Line Interference:** Modeled as narrowband 50/60 Hz sinusoidal interference, reflecting mains power contamination [48].

3) **Laplacian Noise:** Represents impulsive, burst-like noise (e.g., motion artifacts), modeled using a heavy-tailed α-stable distribution [49], [56].

This noise trio was selected for its relevance to physiological recordings, analytical tractability, and ability to span both stochastic and structured distortion types.

C. THALAMIC EEG DATASET

We analyzed a curated dataset of depth EEG recordings from the anterior nucleus of the thalamus (ANT) acquired during seizure and non-seizure states [9]. Thirteen patients with drug-resistant temporal lobe epilepsy contributed a total of 84 seizures, enabling robust intra- and inter-patient variability analysis.

All procedures were approved by the Institutional Review Board of the University of Alabama at Birmingham (IRB-170323005). Informed consent was obtained from all participants, including specific approval for thalamic implantation for research purposes. Details of the multistep consenting process are available in [57].

The recordings were acquired during clinical SEEG monitoring for epilepsy surgery. Demographic details are provided in Table 1 of [9], and electrode implantation, recording protocols, and seizure annotation procedures are described in [9].

D. COMPLEXITY MEASURES EVALUATED

Having established the datasets and signal models, we next describe the complexity metrics evaluated in this study.

We evaluated two symbolic compression-based complexity measures:

- **Lempel-Ziv Complexity (LZC)** [58]
- **Effort-To-Compress (ETC)** [15]

1) LZC

Lempel-Ziv Complexity (LZC) is a compression-inspired complexity measure introduced by Lempel and Ziv [58]. It quantifies the number of distinct substrings, or "phrases," encountered during a left-to-right parsing of a symbolic sequence. Given a time series, it is first converted into a symbolic sequence through binning, as described in Section II-E. The symbolic sequence is then parsed to construct a dictionary of substrings. The size of this dictionary determines the LZ complexity.

Let c denote the dictionary size, m the length of the sequence, and α the number of distinct symbols. LZC is computed as:

$$(c/m * log_{\alpha}(m)$$

This metric reflects the degree of information content or irregularity of a sequence.

Example 1:

For the sequence '001011', parsing yields the dictionary: '0', '01', and '011'. Hence, $c = 3$, $m = 6$, $\alpha = 2$, and the LZC is:

$$LZC = \frac{3}{6 * log_2(6)} \approx 1.2925$$

Example 2:

For the sequence '012310' (derived from 4-bin symbolization), the dictionary is '0', '1', '2', '3', '10'. Here, $c = 5$, $m = 6$, $\alpha = 4$, and:

$$LZC = \frac{5}{6 * log_4(6)} \approx 1.0771$$

Note: LZC emphasizes pattern novelty but does not involve actual compression or sequence reconstruction.

2) ETC

Effort-To-Compress (ETC) quantifies the complexity of a symbolic sequence as the number of iterations required to reduce it to a constant sequence using a symbolic compression algorithm known as Non-Sequential Recursive Pair Substitution (NSRPS) [59].

Given a symbolic sequence (obtained by binning the time series), the algorithm repeatedly substitutes the most frequent pair of adjacent symbols with a new symbol. If no pair occurs more than once, the first pair is substituted. This process continues iteratively until the sequence reduces to a single unique symbol.

Let M be the number of iterations required and N the length of the original sequence. ETC is computed as:

$$ETC = \frac{M}{N-1}$$

By definition, $ETC \in (0, 1]$, since at least one substitution is always needed. The value reflects structural redundancy: more structure requires more iterations.

Example 1:

For the sequence '001011', the steps are: - Replace '01' (most frequent) → '0 2 2 1' - No repeating pairs → replace first '02' → '3 2 1' - Continue: '4 1' → '5' (done)

Total substitutions: $M = 4, N = 6 \rightarrow$

$$ETC = \frac{4}{5} = 0.8$$

Example 2:

For the sequence '012310' (from 4 bins): - No repeating pairs → replace '01' → '4 2 3 1 0' - Continue: '42' → '5 3 1 0' → '63 1 0' → '7 1 0' → '8 0' → '9' (done)

Total substitutions: $M = 5, N = 6 \rightarrow$

$$ETC = \frac{5}{5} = 1.0$$

Note: ETC reflects structural complexity, not computational effort. A higher ETC indicates more internal pattern diversity.

Before applying LZC and ETC, the continuous-valued signals must be converted into symbolic sequences via binning. The choice of bin count directly affects complexity estimation and is thus explored next.

E. SYMBOLIZATION AND BINNING

Before applying complexity measures, all continuous-valued signals were discretized into symbolic sequences. This was achieved using uniform-width binning across the dynamic range of each signal segment, with each bin mapped to a unique symbol (e.g., '0', '1', '2', '3' in the case of 4 bins).

To evaluate the impact of binning granularity on discriminative performance, we empirically assessed the effectiveness of two compression-based complexity measures—ETC and LZC—across varying bin counts (2, 4, 6, and 8). We used paired t-tests to quantify the statistical separability between physiological conditions (seizure vs. non-seizure in thalamic EEG) under noise-free settings.

As shown in Figure 1, both ETC and LZC exhibited marked improvements in separability when the bin count increased from 2 to 4. However, gains plateaued beyond 4 bins, suggesting diminishing returns. This trend was consistent across signal types and datasets. Moreover, increasing bin counts beyond four incurs higher computational and memory costs due to the expanding symbolic alphabet size.

Based on these observations, we selected a 4-bin scheme as an optimal trade-off, offering sufficient symbolic resolution to capture structural complexity while maintaining computational efficiency.

The signals analyzed in this study were sampled 512 Hz for thalamic EEG (recorded from intracranial depth electrodes). Although the 512 Hz EEG sampling rate preserves detailed waveform morphology, the high value may introduce temporal redundancy, which could influence the efficacy of symbolic binning. Investigating the impact of sampling rate on binning effectiveness remains an open direction for future work.

Note on Computational Complexity: Although ETC relies on the Non-Sequential Recursive Pair Substitution (NSRPS) algorithm—which has a theoretical time complexity that scales with sequence length—it remains computationally practical for the relatively short sequences used in this study (typically $<$ 10,000 samples). Unlike entropy-based methods, ETC requires no parameter tuning. Its strengths—including large effect sizes, robustness to noise, and clear physiological interpretability—justify the computational cost. In practice, early stopping criteria and parallel implementations can further reduce runtime, making ETC suitable for clinical or offline applications [60].

To improve the robustness and physiological relevance of complexity measures, we next examine two commonly used preprocessing methods that extract multiscale or differential structure from the signals.

F. PREPROCESSING METHODS: DWT AND DPCM

We evaluated two preprocessing strategies to assess whether transforming signals before complexity estimation could enhance physiological separability.

- **Discrete Wavelet Transform (DWT)**: Performed with a 6-level Daubechies-4 wavelet. DWT decomposes the signal into time-localized frequency components, potentially isolating relevant patterns at different temporal scales. Complexity was computed using either all coefficients, only approximation coefficients, or level-specific detail coefficients.
- **Differential Pulse Code Modulation (DPCM)**: A predictive compression technique where the difference between consecutive samples is symbolized and analyzed. This emphasizes local temporal variations and suppresses slow drifts, potentially making residual complexity more salient.

Although DWT and DPCM are not complexity measures per se, their ability to enhance feature separability was tested by adding them as preprocessing steps before applying compression complexity algorithms. However, as detailed in Section III-B, DPCM preprocessing did not enhance the discriminative performance of complexity measures and is thus not emphasized in the main results.

G. STATISTICAL ANALYSIS AND VALIDATION

We conducted a two-pronged statistical analysis to assess the robustness and discriminative power of complexity measures under various preprocessing strategies and noise conditions.

- **Paired t-test** was used to assess the statistical significance of differences between healthy and pathological states. This test accounts for matched or repeated measurements from the same subjects, making it suitable for our within-subject biomedical data.
- **Cohen's** d Cohen's d was calculated to quantify the magnitude of difference between physiological states, independent of sample size. This standardized effect size complements the t-test by providing insight into practical significance.

All analyzes were implemented using MATLAB (Statistics and Machine Learning Toolbox) and Python (SciPy and NumPy libraries), ensuring reproducibility and cross-platform validation. A Python implementation for computing the paired t-test and Cohen's d on a sample input dataset is provided in Appendix B.

The next section presents our comparative results across synthetic and real-world thalamic EEG data, highlighting the role of preprocessing and complexity in detecting pathological transitions.

III. RESULTS AND ANALYSIS

This section presents a comprehensive evaluation of the compression-based complexity measures ETC and LZC—across both synthetic signal constructs and real-world thalamic EEG datasets. The analysis is organized into two tiers:

- **Synthetic canonical signals**: Chirp, amplitude-modulated chirp, and multi-harmonic waveforms were used to examine the baseline sensitivity of complexity metrics to structured variation under fully controlled conditions, with and without additive noise.

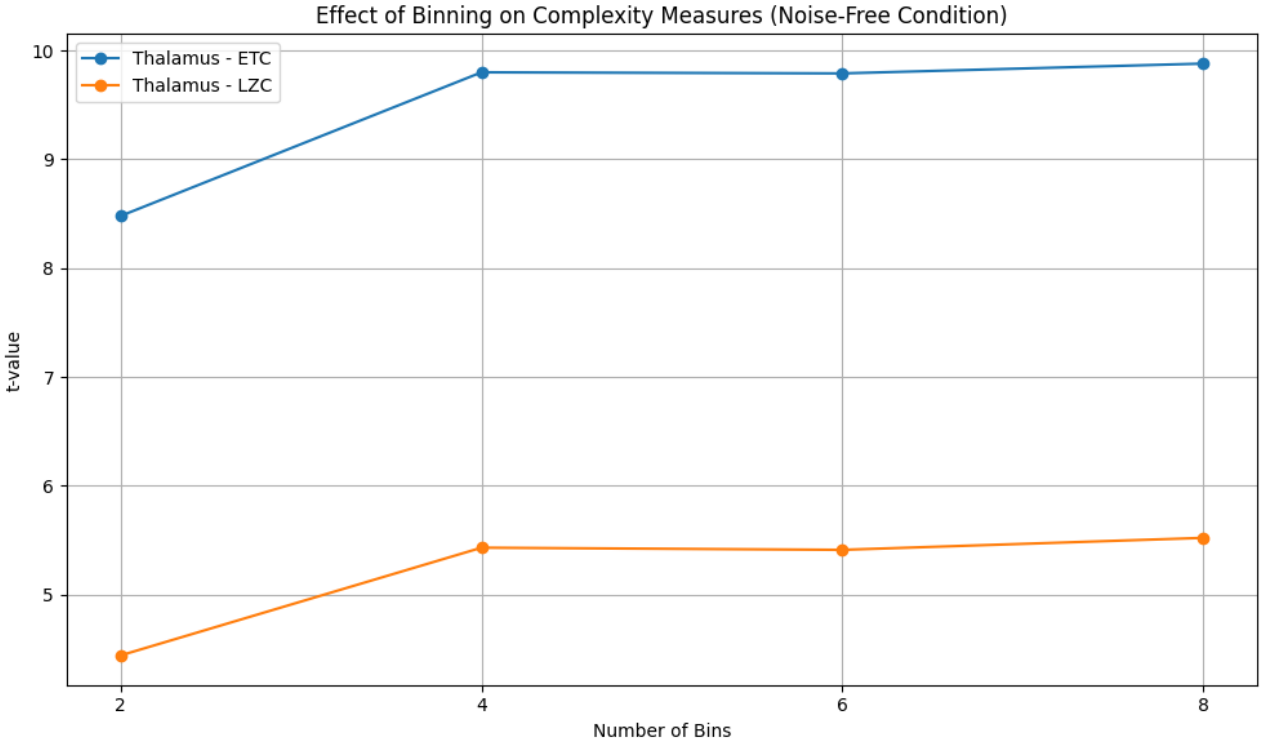

FIGURE 1. Effect of bin count on t-statistic values obtained using ETC and LZC for distinguishing physiological states under noise-free conditions in thalamic EEG datasets.

- **Thalamic EEG recordings**: Clinically acquired signals from the anterior nucleus of the thalamus (ANT) were analyzed to test the discriminative capacity of complexity measures in distinguishing seizure and non-seizure states under real-world noise and inter-subject variability.

Across both domains, we evaluated complexity under clean and noisy conditions. In the clinical EEG case, we further assessed the effects of preprocessing techniques—particularly DWT—on discriminative performance. Statistical comparisons between pathological and non-pathological states were assessed using paired t-tests, and Cohen's d was used to quantify effect sizes.

A. SYNTHETIC SIGNALS: CLEAN VS. NOISY CONDITIONS

We first analyzed synthetic signal models—including chirp signals, amplitude-modulated (AM) chirps, and variable harmonic signals—as introduced in Section II-A. These signals offer a controlled testbed to validate whether complexity measures respond consistently to structural modulations and noise perturbations.

Figures 2 to 4 show the behavior of ETC and LZC for each signal class, under both clean (solid lines) and noisy (dotted lines, Gaussian noise at 20 dB SNR) conditions.

Observations and Interpretation:

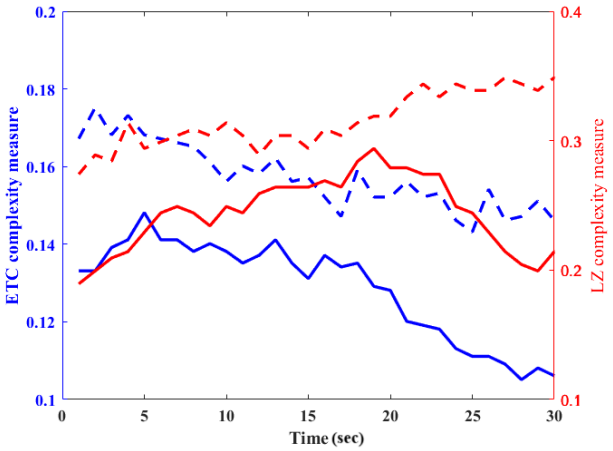

FIGURE 2. Windowed complexity analysis of a chirp signal using ETC and LZC. The signal has a smoothly increasing frequency but retains high temporal predictability. Both measures show stable complexity values over time, with slight increases under 20 dB Gaussian noise. ETC (blue) demonstrates more consistent tracking of noise effects than LZC (red).

The trends across synthetic signals confirm the ability of both ETC and LZC to capture meaningful structural complexity:

- **Chirp signals**: Despite increasing frequency, the waveform remains deterministic and highly predictable. Both ETC and LZC exhibit flat complexity profiles. Under

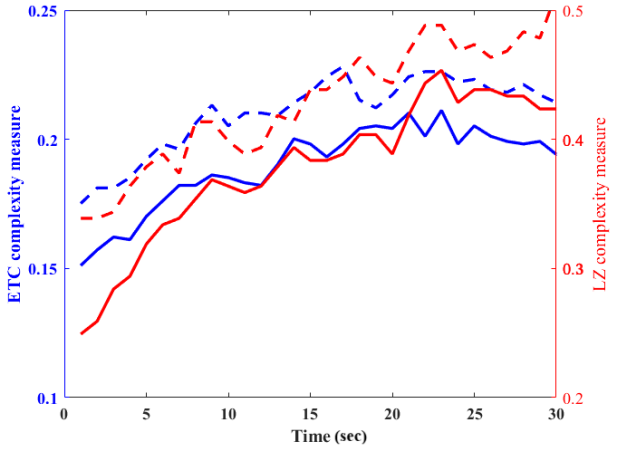

FIGURE 3. ETC and LZC values for an amplitude-modulated chirp signal, with and without 20 dB Gaussian noise. Increasing modulation index introduces richer amplitude variation and structural irregularity. Both complexity measures increase accordingly, capturing these features reliably under noise.

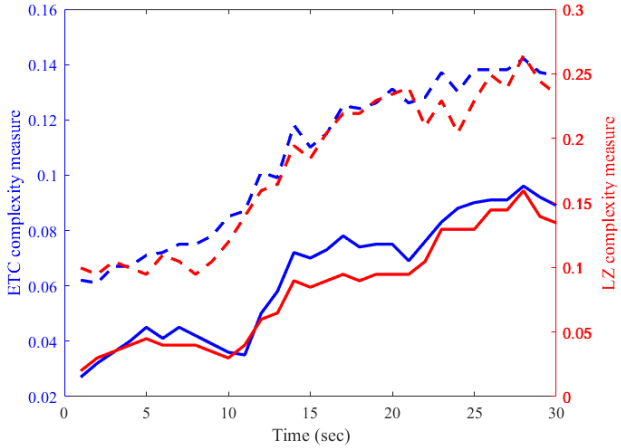

FIGURE 4. Complexity profiles for signals with increasing harmonic content. As the number of harmonics increases, both ETC and LZC show rising trends in complexity, consistent with the greater spectral richness and reduced predictability of the signal. Noise effects (dotted lines) are also reflected by both measures.

20 dB Gaussian noise, ETC better tracks subtle deviations than LZC, suggesting improved noise sensitivity.

- **AM chirps**: As modulation depth increases, amplitude variability becomes more pronounced. Both complexity measures increase accordingly, reflecting the growing structural richness. The trends persist under noise, validating robustness.
- **Variable harmonics**: Complexity increases with the addition of harmonic components. ETC and LZC both show monotonic rises, confirming sensitivity to spectral diversity. As with AM chirps, noise elevates complexity slightly, but preserves relative ordering.

These results demonstrate that both complexity measures reliably detect increased structural variation in idealized signals. While LZC and ETC respond similarly under clean conditions, ETC exhibits superior stability and responsiveness under moderate noise, particularly in chirp signals.

Additional experiments with power-line interference and Laplacian (impulsive) noise yielded comparable trends and are reported in Appendix A, Figures 7 to 12.

TABLE 1. Class-wise descriptive stats, 95% CI and t values for LZC and ETC under different noise conditions (Thalamus, raw signals).

Noise	Measure	Seizure vs. Non-Seizure Statistics
Noise-Free	LZC	Mean ± SD: 0.25 ± 0.13 vs. 0.32 ± 0.13 95% CI: [0.23, 0.27] vs. [0.29, 0.34] $t = 5.63$
	ETC	Mean ± SD: 0.09 ± 0.04 vs. 0.11 ± 0.04 95% CI: [0.08, 0.09] vs. [0.10, 0.12] $t = 5.87$
Gaussian	LZC	Mean ± SD: 0.28 ± 0.12 vs. 0.33 ± 0.12 95% CI: [0.26, 0.29] vs. [0.31, 0.35] $t = 5.56$
	ETC	Mean ± SD: 0.09 ± 0.03 vs. 0.12 ± 0.04 95% CI: [0.09, 0.10] vs. [0.11, 0.12] $t = 5.43$
Powerline	LZC	Mean ± SD: 0.25 ± 0.13 vs. 0.32 ± 0.13 95% CI: [0.23, 0.27] vs. [0.29, 0.34] $t = 6.17$
	ETC	Mean ± SD: 0.09 ± 0.04 vs. 0.11 ± 0.04 95% CI: [0.08, 0.09] vs. [0.10, 0.12] $t = 6.03$
Laplacian	LZC	Mean ± SD: 0.27 ± 0.14 vs. 0.34 ± 0.13 95% CI: [0.24, 0.29] vs. [0.32, 0.36] $t = 6.73$
	ETC	Mean ± SD: 0.09 ± 0.04 vs. 0.12 ± 0.04 95% CI: [0.09, 0.10] vs. [0.11, 0.12] $t = 6.74$

B. THALAMIC EEG: COMPLEXITY IN CLINICAL RECORDINGS

Having validated the sensitivity and noise robustness of ETC and LZC using canonical synthetic signals, we next turn to real-world thalamic EEG recordings. These depth electrode signals—acquired from the anterior nucleus of the thalamus (ANT)—offer an opportunity to evaluate the discriminative power of compression complexity metrics in distinguishing seizure (ictal) from baseline (non-ictal) activity under realistic clinical noise conditions.

We assess performance under four noise scenarios: noise-free, Gaussian, power-line, and Laplacian noise. Additionally, we investigate whether multiscale preprocessing (via DWT) enhances discrimination, and compare ETC and LZC with widely used entropy-based complexity measures.

1) DISCRIMINATION USING RAW SIGNAL COMPLEXITY

a: STATISTICAL SIGNIFICANCE VIA T-TESTS

Table 1 presents a comprehensive statistical comparison of ETC and LZC values between seizure and non-seizure segments in raw thalamic EEG data, under various noise conditions. For both metrics, paired t-tests revealed statistically

TABLE 2. Cohen's *d* values for ETC and LZC without preprocessing (Thalamus dataset).

Noise Type	Raw LZC	Raw ETC
Noise-Free	0.47	0.51
Gaussian Noise	0.43	0.42
Powerline Noise	0.52	0.51
Laplacian Noise	0.62	0.63

TABLE 3. *t*-statistics for ETC and LZC after DWT(all) preprocessing (Thalamus dataset).

Noise Type	DWT(all) + LZC	DWT(all) + ETC
Noise-Free	4.21	12.96
Gaussian Noise	4.04	13.04
Powerline Noise	3.31	15.10
Laplacian Noise	5.22	23.11

significant differences ($p < 0.001$) across all conditions. This affirms the sensitivity of compression-based measures—particularly ETC—to ictal transitions in noisy, real-world EEG signals.

b: EFFECT SIZE ANALYSIS

Cohen's d values, reported in Table 2, indicate moderate discriminative strength in the raw signal setting. ETC slightly outperforms LZC under noise-free and Laplacian conditions, whereas LZC has marginally better performance under Gaussian and power-line noise.

2) EFFECT OF PREPROCESSING: DWT ENHANCES ETC

a: PREPROCESSING WITH DWT

We tested whether complexity discrimination improves with multiresolution preprocessing. Table 3 shows that applying DWT (all coefficients) substantially increases the t-values for ETC across all noise types, particularly under Laplacian noise (23.11). In contrast, LZC performance declines following DWT, suggesting a mismatch between LZC's formulation and the transformed signal space.

b: COHEN'S d AFTER DWT

Effect size analysis confirms this trend: Table 4 shows that DWT preprocessing boosts ETC's discriminative power substantially (Cohen's $d > 1$ across all conditions). In contrast, LZC's effect sizes drop, suggesting sensitivity to energy redistribution from wavelet decomposition.

c: SUMMARY OF OBSERVATIONS

While both complexity measures demonstrate statistically significant separation between ictal and non-ictal thalamic EEG segments, ETC shows more consistent and amplified gains—especially when paired with DWT preprocessing. LZC appears to degrade under DWT, likely due to its reliance on substring diversity, which may be disrupted by multiscale transforms. DPCM preprocessing yielded no clear benefits and is excluded for brevity.

TABLE 4. Cohen's *d* values for ETC and LZC after DWT(all) preprocessing (Thalamus dataset).

Noise Type	DWT(all) + LZC	DWT(all) + ETC
Noise-Free	0.36	1.01
Gaussian Noise	0.31	1.01
Powerline Noise	0.26	1.16
Laplacian Noise	0.40	1.78

C. COMPARISON WITH ENTROPY-BASED COMPLEXITY MEASURES

To position the performance of compression-based complexity metrics (ETC and LZC), we compared them against four established entropy measures: Shannon Entropy, Approximate Entropy (ApEn), Sample Entropy (SampEn), and Permutation Entropy (PermEn). Parameter settings followed standard conventions (ApEn and SampEn: embedding dimension 3, tolerance $0.2 \times$ SD; PermEn: order 3, delay 1).

The results in Table 5 provide a detailed comparison of compression-based and entropy-based complexity measures on raw thalamic EEG signals across various noise types. Overall, entropy-based measures—particularly ApEn and SampEn—show strong discriminability under clean and structured noise conditions. Compression-based measures, especially ETC, also show reliable performance and maintain stable effect sizes across all noise types. Notably, ETC demonstrates its highest robustness under impulsive noise (Laplacian), Shannon Entropy, in contrast, fails to capture meaningful complexity distinctions and often yields negligible or negative effect sizes.

1) EFFECT OF PREPROCESSING ON COMPLEXITY MEASURES

To further evaluate how different preprocessing strategies influence complexity-based discrimination, we analyzed the performance of four methods—**DWT(all)**, **DWT(approximate)**, **DWT(L5)**, and **DPCM)**—in the Thalamic EEG dataset. Table 6 summarizes the corresponding t-statistics and Cohen's d values across noise types for all complexity measures.

Key Findings:

- **DWT(all)** emerged as the most effective preprocessing strategy. It significantly boosted the discriminability of ETC, yielding large effect sizes across all noise conditions (all $d > 1.0$), peaking at $d = 1.78$ under Laplacian noise.
- **Entropy-based measures responded variably to DWT(all)**. While Shannon entropy showed slight gains, ApEn degraded sharply, showing reversed or negative effect sizes. Sample Entropy remained relatively stable, with minor improvements under specific conditions.

TABLE 5. Comparison of *t*-values and Cohen's *d* for different measures under noise (Thalamus dataset, raw signals).

Dataset	Noise Type	ETC		LZC		ShanEn		ApEn		SampEn		PermEn	
		t	d	t	d	t	d	t	d	t	d	t	d
Thalamus	Noise-Free	5.87	0.51	6.03	0.47	-0.60	-0.05	6.61	0.51	6.49	0.50	5.44	0.42
	Gaussian Noise	5.43	0.42	5.56	0.43	-0.90	-0.07	7.31	0.56	6.95	0.54	4.91	0.38
	Power Line	6.03	0.51	6.17	0.52	-0.62	-0.05	6.65	0.51	6.53	0.50	1.41	0.11
	Laplacian	6.74	0.63	6.73	0.62	-1.46	-0.11	7.50	0.58	7.28	0.56	6.15	0.47

- **DWT(approximate)** and **DWT(L5)** offered modest benefits only in select cases. For instance, SampEn improved slightly under DWT(L5) in Laplacian noise ($d = 0.31$), but these strategies did not yield consistent gains across metrics or noise types. ETC and LZC were unaffected or degraded by these partial decompositions.
- **DPCM** preprocessing was largely ineffective. It produced marginal improvements in Shannon entropy under structured noise but often degraded ApEn, PermEn, and compression-based metrics. ETC and LZC showed negligible or negative changes with DPCM.

2) SUMMARY AND IMPLICATIONS

This comparative evaluation reinforces that no complexity measure or preprocessing approach is universally optimal. Effectiveness depends strongly on signal modality, noise characteristics, and the nature of the metric.

- **Compression-based measures**, particularly ETC, demonstrated superior robustness and discriminative power for thalamic EEG. When paired with **DWT(all)**, ETC consistently delivered high effect sizes and was resilient across all noise types, including impulsive noise.
- **Entropy-based measures**, such as SampEn and ApEn, performed competitively under raw conditions but were more sensitive to preprocessing. In particular, ApEn showed marked deterioration after wavelet-based transformations.
- **Preprocessing choice is critical. Full multiscale decomposition (DWT(all))** provides the most substantial benefits, especially for compression complexity. Other methods like DWT(L5) or DPCM yield inconsistent or marginal improvements and may even degrade certain measures.
- **Noise resilience varies by metric class.** Compression-based complexity is more robust under impulsive and mixed noise conditions. Entropy-based measures, while sometimes more sensitive to subtle structure in clean signals, are more affected by preprocessing and noise.

These findings point out the need for **modality-aware and noise-aware selection** of complexity measures. For clinical EEG applications such as seizure detection from thalamic recordings, ETC combined with DWT(all) preprocessing offers a reliable, interpretable, and noise-tolerant framework. In contrast, entropy-based metrics like SampEn may be better suited to smoother or lower-frequency signals, provided preprocessing is minimized or carefully selected.

IV. DISCUSSION

This study systematically evaluated compression-based complexity measures—ETC and LZC—in comparison with classical entropy-based metrics (Shannon, Approximate, Sample, and Permutation Entropy) for distinguishing pathological from normal physiological states in thalamic EEG recordings and controlled synthetic signals. The results demonstrate that no single metric is universally superior: performance depends strongly on signal structure, noise characteristics, and preprocessing strategy. Nevertheless, ETC consistently emerged as the most robust and noise-tolerant measure, particularly when paired with multiscale preprocessing via the Discrete Wavelet Transform (DWT).

A. FROM SYNTHETIC VALIDATION TO CLINICAL EEG

Analyses on synthetic signals—chirp, amplitude-modulated chirp, and variable-harmonic waveforms—confirmed that both ETC and LZC capture systematic increases in structural complexity associated with richer signal composition. These controlled tests established their theoretical validity and provided a baseline for interpreting EEG results under real-world noise. In the thalamic EEG dataset, both measures successfully discriminated seizure from non-seizure states, with ETC exhibiting slightly higher effect sizes and stronger resilience to noise.

B. MODALITY-DEPENDENT PERFORMANCE

Compression-based measures proved particularly effective for thalamic EEG, where symbolic redundancy and multiscale oscillatory dynamics are prominent. ETC showed the most consistent discrimination, achieving large effect sizes even under impulsive noise ($d = 0.63$ on raw data, $d = 1.78$ after DWT). Entropy-based metrics such as Sample Entropy and Approximate Entropy remained competitive under clean conditions but were more sensitive to preprocessing and noise. These results indicate that compression measures are better suited to short, noisy, and nonstationary neural recordings, whereas entropy-based measures may perform well in smoother or lower-frequency physiological signals.

TABLE 6. *t*-values (top) and Cohen's *d* (bottom) for preprocessed complexity measures under noise.

Data	Noise	DWT(all)		DWT(approx)		DWT(L5)		DPCM	
		t	d	t	d	t	d	t	d
Shannon Entropy									
Thal	Clean	5.45	0.42	1.75	0.14	1.62	0.12	1.41	0.11
	Gaussian	4.25	0.33	1.2	0.09	1.9	0.15	1.66	0.13
	Powerline	5.04	0.39	1.2	0.09	1.9	0.15	3.34	0.26
	Laplacian	5.09	0.39	1.43	0.11	1.59	0.12	3.22	0.25
Approximate Entropy (ApEn)									
Thal	Clean	-5.19	-0.4	2.32	0.18	-4.28	-0.33	0.46	0.04
	Gaussian	-5	-0.39	2.23	0.17	-4.97	-0.38	0.99	0
	Powerline	-4.59	-0.35	2.23	0.17	-4.97	-0.38	1.41	0.11
	Laplacian	-5.41	-0.42	2.26	0.17	-4.82	-0.37	1.45	0.11
Sample Entropy (SampEn)									
Thal	Clean	2.26	0.17	2.07	0.16	2.97	0.23	0.33	0.03
	Gaussian	3.01	0.23	2.04	0.16	2.41	0.19	0.85	0.07
	Powerline	1.76	0.14	2.04	0.16	2.41	0.19	1	0.08
	Laplacian	2.6	0.2	2.86	0.22	3.96	0.31	1.07	0.08
Permutation Entropy (PermEn)									
Thal	Clean	-1.05	-0.08	-1.27	0.1	1.5	0.12	0.4	0.03
	Gaussian	0.74	0.06	0.03	0	2.88	0.22	0	0
	Powerline	-0.64	-0.05	0.03	0	2.88	0.22	1.73	0.13
	Laplacian	1.07	0.08	0.03	0	1.91	0.15	2.99	0.23
Lempel-Ziv Complexity (LZC)									
Thal	Clean	4.21	0.36	-1.68	-0.13	2.33	0.18	0.78	0.06
	Gaussian	4.04	0.31	-1.79	-0.14	2.13	0.16	0.95	0.07
	Powerline	3.31	0.26	-1.79	-0.14	2.13	0.16	0.93	0.07
	Laplacian	5.22	0.40	-1.39	-0.11	2.63	0.20	1.67	0.13
Effort-to-Compress (ETC)									
Thal	Clean	12.96	1.01	-1.23	-0.1	1.48	0.11	-0.05	0
	Gaussian	13.04	1.01	-1.15	-0.09	1.91	0.15	0.04	0
	Powerline	15.10	1.16	-1.15	-0.09	1.91	0.15	0.07	0.01
	Laplacian	23.11	1.78	-0.34	-0.03	2.42	0.19	0.73	0.06

C. NOISE STRUCTURE MATTERS

The effect of noise on complexity estimation varied across metrics:

- Under **structured noise** (Gaussian, powerline), both ETC and Sample Entropy maintained high discriminative power.
- Under **impulsive noise** (Laplacian), entropy measures—particularly ApEn—often degraded or reversed direction, while ETC retained moderate-to-strong effect sizes.
- Shannon Entropy showed limited ability to capture meaningful changes in EEG complexity, reflecting its insensitivity to nonlinear temporal dependencies.

These findings confirm that compression-based measures offer superior robustness to diverse noise profiles, an essential property for real-world EEG analysis.

D. PREPROCESSING EFFECTS AND MULTISCALE ENHANCEMENT

Wavelet-based preprocessing (DWT) had a pronounced impact on performance. Using all wavelet coefficients [DWT(all)] substantially amplified ETC's discriminative strength, yielding large and stable effect sizes across all noise types. This suggests that multiscale decomposition enhances the visibility of structural irregularities that ETC effectively compresses. By contrast, partial decompositions such as DWT(L5) or DWT(approximate) provided only marginal improvements for entropy measures and inconsistent effects for compression metrics. DPCM offered limited or no benefit, underscoring that not all transformations align well with symbolic compression frameworks.

E. INTERPRETABILITY VS. PERFORMANCE

While entropy-based measures provide physiological interpretability—being grounded in the notion of predictability—they require careful parameter tuning and are sensitive to data length and noise type. Compression measures like ETC, in contrast, are parameter-free, computationally simple, and more stable under varying conditions. Their symbolic nature, though less physiologically direct, offers robustness and generalizability, making them attractive for embedded or online applications.

F. COMPUTATIONAL CONSIDERATIONS

Both ETC and LZC are computationally efficient, involving simple symbolic or dictionary-based operations. ETC's iterative substitution process is linear in sequence length and does not rely on floating-point operations or parameter estimation. These traits make compression-based complexity particularly suitable for real-time or resource-limited applications such as implantable or bedside EEG monitoring systems. Future work could quantify execution time and memory footprint across longer signals and adaptive symbolization schemes to further validate their real-time feasibility.

G. LIMITATIONS

Despite promising performance, several limitations merit attention. ETC's recursive substitution may become computationally intensive for very long sequences. Moreover, its link to underlying physiological processes is indirect, emphasizing structural rather than dynamical properties. Fixed binning and predefined wavelet configurations were used in this study; adaptive binning or data-driven wavelet selection could enhance sensitivity. Finally, while the dataset captures representative thalamic activity, future work should extend validation to other deep-brain or cortical regions.

H. CLINICAL RELEVANCE

From a clinical standpoint, these results emphasize the value of noise- and modality-aware selection of complexity pipelines. For thalamic EEG–based seizure detection, ETC combined with DWT(all) preprocessing provided the highest discriminability (Cohen's $d = 1.78$; accuracy $= 87.5\%$), while remaining interpretable and computationally efficient. This supports its use as a candidate feature for adaptive neurostimulation or monitoring frameworks. Entropy measures, particularly Sample Entropy, may still offer complementary insights into smoother, low-frequency dynamics but require cautious parameter and preprocessing choices.

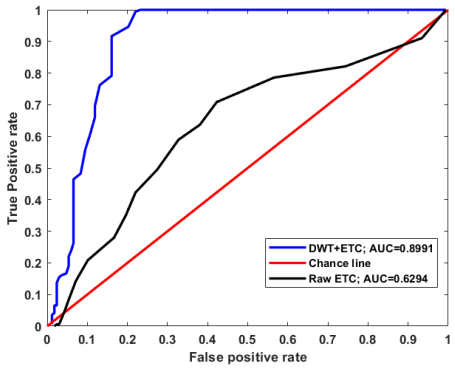

FIGURE 5. ROC curves for ETC under noise-free conditions, with and without DWT preprocessing.

I. TRANSLATIONAL EVALUATION: FROM COMPLEXITY TO CLASSIFICATION

To complement our statistical and effect size analyses, we conducted a threshold-based binary classification using the compression complexity measures—ETC and LZC—to evaluate their practical discriminability in identifying seizure states from thalamic EEG data. The classification threshold was computed as the midpoint between the mean complexity values of the two classes. A sample was labeled as pathological if its complexity value fell below this threshold, reflecting the hypothesis that seizure states are typically characterized by reduced complexity compared to normal brain dynamics. This approach avoids reliance on complex machine learning models and emphasizes the discriminative potential of the complexity measures themselves.

We computed three clinically relevant performance metrics:

- **Accuracy:** the proportion of total correctly classified samples.
- **Recall (Sensitivity):** the proportion of seizure samples correctly identified.
- **Precision:** the proportion of positively classified samples that were true seizures.

Table 7 summarizes the performance of both measures—across clean and noisy conditions, with and without DWT preprocessing—in terms of classification accuracy, recall (sensitivity), and precision.

1) FINDINGS

On raw EEG data, both ETC and LZC yielded balanced classification performance, with accuracies centered around

TABLE 7. Accuracy, Recall, and Precision (%) for ETC and LZC with and without DWT preprocessing.

Dataset	Condition	ETC			LZC		
		Accuracy	Recall	Precision	Accuracy	Recall	Precision
Thalamus (Raw)	Noise-Free	63.1	63.3	63.8	62.5	63.1	62.4
	Gaussian Noise	63.4	64.3	63.2	64.0	66.1	63.4
	Powerline Noise	63.4	63.1	63.5	63.1	64.3	62.8
	Laplacian Noise	63.4	61.9	63.8	63.4	63.1	63.5
Thalamus + DWT (all) preprocessed	Noise-Free	81.0	77.4	83.3	61.6	48.2	65.9
	Gaussian Noise	87.5	86.3	88.4	60.4	50.0	63.2
	Powerline Noise	82.1	79.2	84.2	61.3	47.0	65.8
	Laplacian Noise	86.9	85.1	88.3	60.4	45.2	65.0

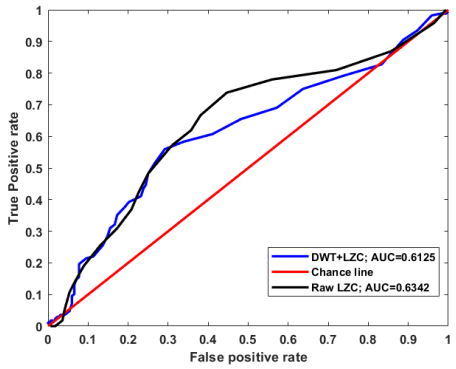

FIGURE 6. ROC curves for LZC under noise-free conditions, with and without DWT preprocessing.

TABLE 8. AUC scores for ETC and LZC under various noise conditions, with and without DWT preprocessing.

Noise Type	Preprocessing	ETC AUC	LZC AUC
Gaussian	Raw EEG	0.6297	0.6462
	DWT	0.9293	0.5908
Powerline	Raw EEG	0.6278	0.6374
	DWT	0.8989	0.6143
Laplacian	Raw EEG	0.6402	0.6420
	DWT	0.9173	0.6172

63% across all noise conditions. This reinforces their stability under noisy, unprocessed conditions and validates their statistical discriminability in the raw signal domain.

However, the impact of DWT preprocessing was starkly different for the two metrics. For ETC, DWT(all) led to a consistent increase in classification performance across all noise types:

- Accuracy improved from 63.4% (Laplacian, raw) to 86.9% (Laplacian, DWT).
- Recall increased to 86.3%, indicating excellent sensitivity to seizure detection.

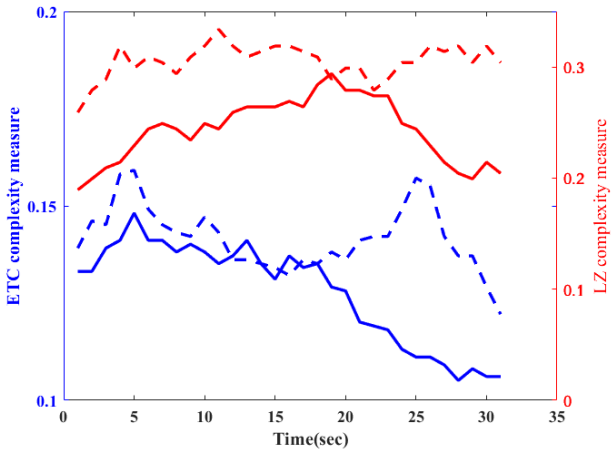

FIGURE 7. Variation of windowed ETC and LZC measures for chirp signal with zero noise and power line noise.

- Precision reached 88.4%, confirming low false positive rates.

In contrast, LZC did not benefit from wavelet preprocessing; its performance slightly declined, with accuracy remaining around 60–61%, and recall dropping in some cases (e.g., 45.2% under Laplacian noise).

To gain a deeper understanding of how reliably each complexity measure distinguishes between seizure and non-seizure states, we also performed a Receiver Operating Characteristic (ROC) analysis. For every condition tested, ROC curves were constructed by gradually adjusting the classification threshold across the full range of observed complexity values. The Area Under the Curve (AUC) served as a summary statistic, capturing the overall separability between classes. In general, a higher AUC suggests better classification performance, as it reflects stronger discriminability that is not dependent on any single threshold choice.

Figures 6 and 5 illustrate the ROC curves for LZC and ETC under noise-free conditions, showing how each measure performs with and without DWT preprocessing. For ETC,

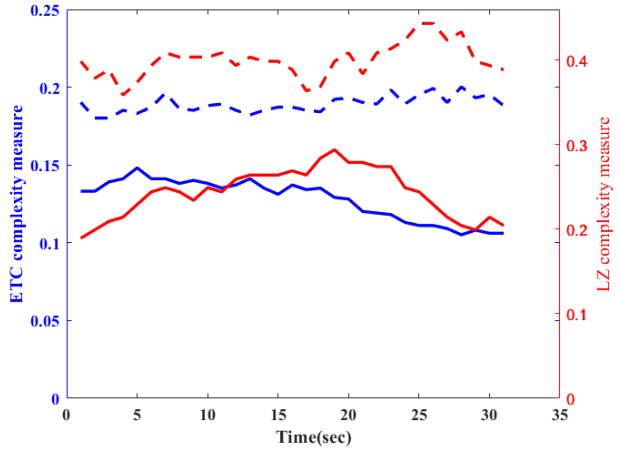

FIGURE 8. Variation of windowed ETC and LZC measures for chirp signal with zero noise and Laplacian noise.

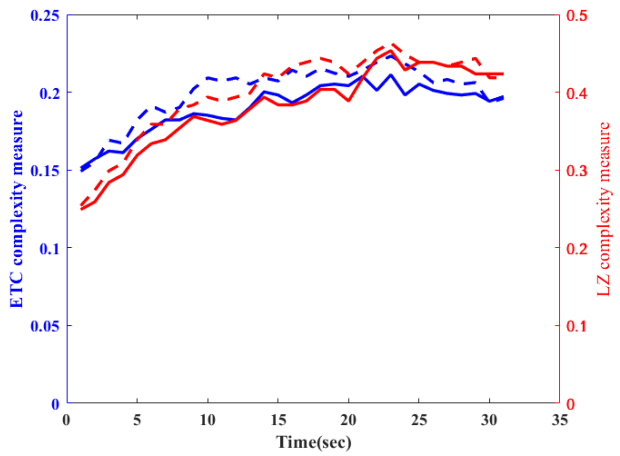

FIGURE 9. Variation of windowed ETC and LZC measures for AM modulated chirp signal with zero noise and powerline noise.

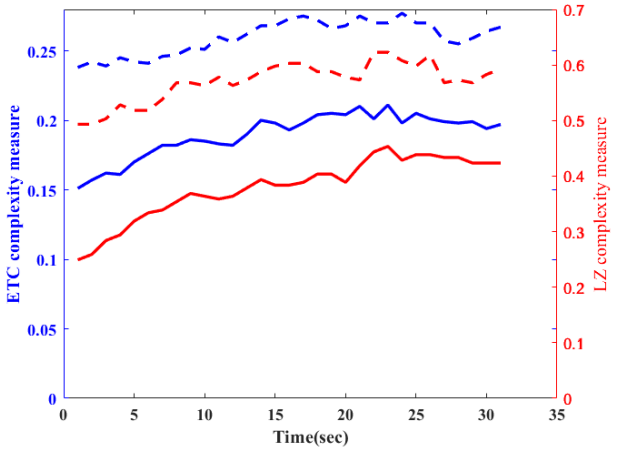

FIGURE 10. Variation of windowed ETC and LZC measures for AM modulated chirp signal with zero noise and Laplacian noise.

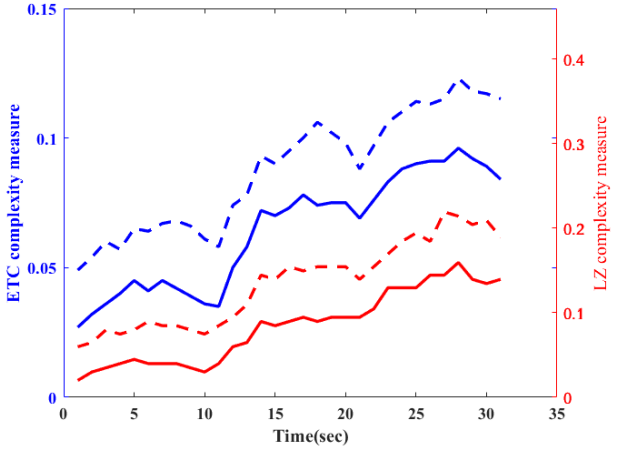

FIGURE 11. Variation of windowed ETC and LZC measures for variable harmonics signal with zero noise and power line noise.

DWT appears to substantially improve class separability, with the AUC rising from 0.6294 to 0.8991 — a notable gain. LZC, on the other hand, showed a modest decrease in AUC after preprocessing (from 0.6342 to 0.6125), suggesting that while DWT benefits ETC, it may slightly disrupt the structure LZC relies on to encode signal complexity.

To better understand how each complexity measure performs under more realistic conditions, we extended the AUC analysis to include three common noise types: Gaussian, Powerline, and Laplacian. The results, summarized in Table 8, show how ETC and LZC behave with and without DWT preprocessing under these noisy settings. Overall, ETC appears to be more resilient to noise, particularly when combined with DWT, consistently showing higher AUC scores. In contrast, LZC showed only modest changes, and in several cases, its performance declined after preprocessing.

2) IMPLICATIONS

These results offer three key insights:

1) ETC with DWT preprocessing achieves the **highest practical classification performance** among all complexity measures tested, under all noise conditions.
2) The improvement in ETC's accuracy, recall, and precision after DWT mirrors its statistical performance gains (e.g., high t-values and large Cohen's d), reinforcing the robustness of this combination.
3) LZC, while effective in raw data, does not benefit from DWT in the same way—highlighting the importance of measure-specific preprocessing.

3) CONCLUSION

This threshold-based evaluation demonstrates that ETC, especially when paired with DWT preprocessing, not only achieves strong statistical separability but also translates into

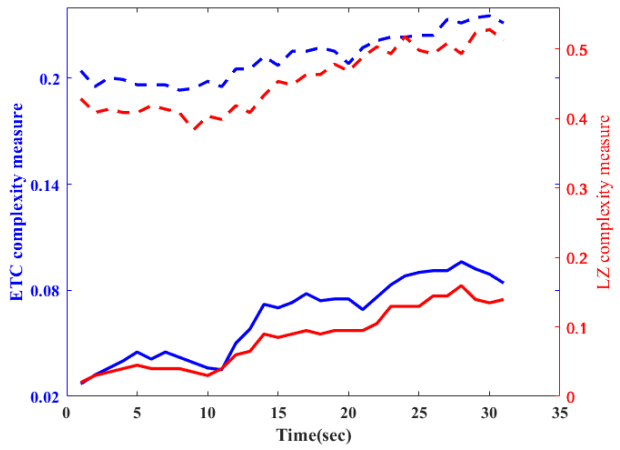

FIGURE 12. Variation of windowed ETC and LZC measures for variable harmonics signal with zero noise and Laplacian noise.

high classification accuracy, recall, and precision in seizure detection. Its simplicity, interpretability, and resilience across noise conditions position it as a promising candidate for integration into real-time clinical neurodiagnostic systems.

V. CONCLUSION AND FUTURE WORK

This study presented a systematic evaluation of entropy and compression based complexity measures in clinically relevant neurophysiological signals, focusing primarily on thalamic EEG under various noise conditions and preprocessing strategies. Our findings emphasize that the performance of complexity metrics is highly context-specific—governed by the signal modality, noise characteristics, and preprocessing pipeline.

Entropy-based metrics, particularly SampEn, showed strong discriminative power in raw EEG signals, maintaining robustness across noise types. However, their performance was often sensitive to preprocessing choices, with ApEn exhibiting direction reversals under certain noise and signal conditions. Shannon Entropy consistently underperformed, highlighting its limited discriminative utility in this context.

Compression-based measures, especially ETC, emerged as the most reliable and noise-resilient approach for thalamic EEG-based seizure detection. ETC achieved high effect sizes under all noise types—most notably under impulsive (Laplacian) noise—and showed remarkable gains when paired with multiscale preprocessing using Discrete Wavelet Transform (DWT-all). LZC, though robust in raw data, did not benefit from preprocessing to the same extent.

Our results also underscored the importance of preprocessing design. Among the tested pipelines, **DWT(all)** consistently enhanced compression metrics, while selective DWT levels (e.g., L5) improved entropy metrics like SampEn. DPCM, in contrast, offered minimal or inconsistent gains and often degraded performance.

These findings highlight that complexity analysis is not a one-size-fits-all solution. Instead, optimal configurations depend on task-specific requirements, signal dynamics, and noise environments. For seizure detection in EEG, ETC combined with DWT preprocessing offers a robust, interpretable, and parameter-free framework. In contrast, SampEn remains a competitive choice for smoother or low-frequency physiological signals. Entropy and compression approaches should be viewed as complementary perspectives on signal complexity—each offering distinct operational advantages.

Looking ahead, adaptive or hybrid frameworks that dynamically select or combine complexity measures based on real-time signal characteristics could further enhance diagnostic accuracy and clinical applicability in neurocritical care.

A. FUTURE WORK

Several directions emerge from this work:

- **Computational Optimization:** The current ETC implementation, based on Non-Sequential Recursive Pair Substitution (NSRPS), can be optimized for faster execution on long symbolic sequences. Profiling runtime and memory usage of ETC versus other metrics will inform deployment feasibility in embedded or real-time systems.
- **Advanced Symbolic Mappings:** Exploring multiscale, data-driven, or adaptive symbolic quantization strategies may enhance complexity capture in nonstationary or noisy physiological signals.
- **Integration with Learning Frameworks:** Compression complexity measures such as ETC and LZC can be integrated into machine learning pipelines (e.g., SVMs, random forests, deep networks) to enable data-driven classification while retaining interpretability.
- **ETC Model Refinement:** The ETC model can be extended to account for the cost of per-iteration symbolic operations, offering a finer-grained estimate of complexity—especially for long or highly redundant sequences.
- **Clinical Generalization:** Validating these complexity pipelines on multicenter datasets across a range of neurological conditions (e.g., epilepsy, traumatic brain injury, coma, neurodegeneration) will be critical to assess their translational potential.

In conclusion, this study advocates for a noise-aware, modality-sensitive approach to complexity analysis. Compression complexity, particularly ETC with DWT, holds strong promise for real-time, interpretable monitoring in clinical neurophysiology.

APPENDIX A
PERFORMANCE OF COMPLEXITY MEASURES ON SYNTHETIC AND SIMULATED SIGNALS UNDER NOISY CONDITIONS

See Figures 7–12.

APPENDIX B
STATISTICAL ANALYSIS CODE

The following Python code was used to compute the paired t-test and Cohen's d for comparing intracranial pressure (ICP) signals between hypertensive and normal patients:

```
import numpy as np
from scipy.stats import ttest_rel

# Sample ICP data: Hypertension and
Normal hypertension = np.array([\ldots])
normal = np.array([\ldots])

# Paired t-test
t_stat, p_value = ttest_rel(normal,
 hypertension)
# The \text{t-statistic} is computed as:
t = d_avg / (s_d/np.sqrt(n))
# where:
#   $d_avg$  = mean of the differences
(normal - hypertension),
#   s_d = standard deviation of the
 differences,
#   n   = number of paired observations

# Cohen's d
differences = normal - hypertension
mean_diff = np.mean(differences)
std_diff = np.std(differences, ddof=1)
cohens_d = mean_diff/std_diff

This analysis, performed using ETC on
noise-free ICP signals, yielded$:$
\begin{itemize}
    \item Paired $t$-test statistic:
    $t = 10.52$
    \item $p$-value: $3.28
    \times 10^{-13}$
    \item Cohen's $d$: $1.62$
    (large effect size)
\end{itemize}
```

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